RACIAL/ETHNIC DIFFERENCES IN NON-WORK AT WORK

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Evidence from the American Time Use Survey 2003–2012 suggests that minority employees, especially men, spend a small but statistically significant amount of time not working at the workplace relative to non-Hispanic whites. The time differences remain significant but decrease by 25 to 50% when accounting for detailed industry and occupation controls. Union status, public- or private-sector attachment, payment method, and educational attainment do not explain the differences, although health status is important among African Americans. The estimates imply that the differences in non-work at the worksite can explain up to 10% of the adjusted wage gap between minority and non-Hispanic white workers.

Hours on the Job and Hours Working

Commonly used statistics on labor productivity and real wages are usually computed by dividing measures such as earnings by reported hours worked. Commonly reported estimates of (adjusted) wage differentials ("discrimination") across racial-ethnic-gender groups require adjusting weekly earnings for differences in hours worked among these groups. In the United States, usual measures of hours are reported either weekly in the monthly

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Hamermesh thanks the Alexander von Humboldt Stiftung for financial support. Genadek was supported by the Minnesota Population Center (HD041023) and the University of Colorado Population Center (HD066613), funded through the Eunice Kennedy Shriver National Institute for Child Health and Human Development (NICHD). Burda received support from the Collaborative Research Center 649 "Economic Risk" of the Deutsche Forschungsgemeinschaft. We thank Jonah Gelbach for the STATA code, V. Bhaskar, Kevin Carney, Kerwin Charles, Christopher Gallo, Elizabeth Handwerker, Joanne Kleydish, Anna Maria Koukal, Michael Naef, Ronald Oaxaca, and participants in seminars at several universities and conferences for helpful comments. For information regarding the data and/or computer programs used for this study, please address correspondence to hamermes@eco.utexas.edu.

KEYWORDS: discrimination, time use, compensating wage differentials, effort, ethnicity, race

ILR Review, XX(X), Month 201X, pp. 1–21
DOI: 10.1177/0019793919891429.
Journal website: journals.sagepub.com/home/ilr
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household-based Current Population Survey (CPS); weekly, monthly, or annually in other household surveys; or weekly by employers in the monthly Current Employment Statistics (CES).

Use of any of these indicators may produce biased estimates of the outcomes of interest, including time series of changes in labor productivity (examined by Burda, Hamermesh, and Stewart 2013; Burda, Genadek, and Hamermesh 2020), measures of growth in living standards per hour of work, and demographic wage differentials in cross sections. If, for example, hours worked reported by minority or female workers exceed actual hours by less than the average, estimates of adjusted hourly wage/earnings differentials will understate the extent of discriminatory differences in earnings.

Until recently, accounting for this potential difficulty was not possible—no nationally representative data set provided information on what people do during the hours that they report working. The American Time Use Survey (ATUS) (see Hamermesh, Frazis, and Stewart 2005) was the first to do so. It provides diary information on more than 400 possible activities engaged in by large samples of (recent CPS) respondents, including detailed information on various activities undertaken at the workplace. We use these data, collected from 2003 to 2012, to study differences among demographic groups in the fraction of time they spend at the workplace but not working (Hofferth, Flood, and Sobek 2015).

We examine many explanations for these disparities, such as the effects of controlling for demographic differences and industry and occupation indicators. Finding that this reduces racial/ethnic differences on average by about one-third, we investigate whether the effects arise from dissimilarities in reporting behavior. We then calculate how much estimated adjusted wage differentials change when we make further adjustments for racial/ethnic variations in hours reported working at the workplace.

Racial/ethnic differences in employment/population ratios and weekly work hours in the United States are considerable. Among African American men, for example, these differences imply 13% less work per capita, totaling differences in employment and hours, than non-Hispanic white men (authors' calculations are based on the CPS-Merged Outgoing Rotation Groups [MORG] files for 2014 to 2016). These disparities are substantially larger than any for total non-work time at work. While racial/ethnic differences in employment and hours are very well documented, the divergences on which we focus are non-zero and have not been examined to date.

ATUS Measures of Time Use on the Job

As part of its daily diaries, the ATUS includes information on where the respondent was during each of most of the activities undertaken, with one possibility being "at the workplace."[1] Work and work-related activities constitute the primary action for most time spent at the workplace, and we assume that it represents productive time. Respondents, however, also indicated, for example, "eating at work"; "socializing, relaxing, and leisure"; "sports and exercise"; and "security procedures." These categories include employer-sanctioned breaks or self-initiated "downtime" in work schedules. We combine all time spent in primary activities at work categorized as other than work or work-related and divide by reported (in the diary) total time at the workplace to create η, the fraction of time at the worksite that the person is not working. This measure excludes time when the person reports working for pay at a location other than the workplace. Some of these non-work activities might be regarded as productive, as are many off-the-job pursuits (e.g., exercise and sleep). We accept respondents' notions of what constitutes their regular work, as reflected in their diaries, and treat the residual time at the worksite as non-work.

Recollection of non-work at work on the following day might be hazier than some other undertakings of equal duration. Yet, non-work seems at least as easily recollected as time spent in job search as reflected in the ATUS, which has been extensively analyzed in the economics literature (e.g., Aguiar, Hurst, and Karabarbounis 2013). Even if these activities are under-reported or error-ridden, systematic under-reporting or errors by race/ethnicity would be necessary for these potential problems to affect our conclusions. We examine this possibility in some detail when we discuss our results.[2]

The first decade of ATUS diaries, from 2003 to 2012, included more than 135,000 respondents. Because we require diaries from workdays, and because the ATUS oversamples weekend days, far fewer diaries are usable for our purpose. Moreover, since our estimates can form the basis for adjusting wage differentials, measured worker productivity, and other outcomes, we focus only on employees. These exclusions leave us with a sample of 35,548 workers who provided daily diaries for days on which they were at their place of employment. We split the sample by gender, then divide workers in each gender into five mutually exclusive and exhaustive racial/ethnic groups: non-Hispanic white, African American, non-black

[1]For most activities in the ATUS, respondents are asked, "Where were you while you were [ACTIVITY]?" They can report any location while working, including home, restaurant, or the workplace. (This information is obtained regardless of whether the respondent is employed or self-employed. Thus, the self-employed can report working at their workplace while working or elsewhere.) We only include respondents who report some work at the workplace, but we do not remove respondents who report working at the workplace and elsewhere throughout the day.

[2]The mean reported time worked on the diary day accords very well with the usual hours recalled for the previous week (Barrett and Hamermesh 2019). The differences between them are mostly accounted for by days worked, using estimates from the roughly quinquennial May CPS from 1973–1991; this measure suggests variation by race. In any case, because all but the raw fractions of time spent not working at the workplace are adjusted for both reported usual weekly hours and recorded diary work hours, reporting problems of this sort are obviated.

Table 1. Non-Work Time at Work and Ethnic Representation, ATUS Employees, 2003–2012

	Non-Hispanic white	*African American*	*Non-black Hispanic*	*Asian American*	*Other races*
			Men		
Fraction of workplace time not working	0.0645	0.0793	0.0848	0.0679	0.0701
	(0.0022)	(0.0063)	(0.0055)	(0.0099)	(0.0133)
N =	12,348	1,830	2,582	651	366
Share of race/ethnicity in:[a]					
ATUS Sample	0.695	0.102	0.145	0.037	0.021
ACS	0.693	0.097	0.145	0.044	0.021
			Women		
Fraction of workplace time not working	0.0646	0.0758	0.0779	0.0724	0.0649
	(0.0023)	(0.050)	(0.0058)	(0.1050)	(0.1290)
N =	11,877	2,787	2,137	605	365
Share of race/ethnicity in:[a]					
ATUS Sample	0.668	0.156	0.120	0.034	0.022
ACS	0.687	0.127	0.118	0.045	0.023

Notes: Standard errors in parentheses. These means and the estimates reported in Tables 2 to 6 are all based on ATUS final sampling weights. ACS, American Community Survey; ATUS, American Time Use Survey.
[a]Rounded to add to 1.

Hispanic, Asian American, and other races. We classify as non-black Hispanic any respondent whose race is not African American and who lists ethnicity as Hispanic.

In Table 1 we present estimates of η, the fraction of time at the worksite not working, by gender and racial/ethnic group, constructed as means using ATUS final weights. Overall, the mean fraction of time at work spent not working is 0.069. Substantial differences exist, however, in the η within each gender across the groups, with non-Hispanic whites reporting less non-work time per hour at work than other groups. These differences do not account for the demographic or other variations across groups that we explore in the next section.

There is no perfect external verification of these numbers, and therefore exact comparisons are not possible. The ATUS is the only time-diary survey anywhere to offer such a highly detailed breakdown of time spent at the workplace. An Internet survey conducted in 2012, however, provides a bit of corroborating evidence (Salary.com 2018). Although we create our measure of non-work from daily time-diaries, that survey directly asked employees about time wasted at work. It also focused on time spent on the computer, which is more difficult to capture and measure using our data. Yet despite the different method and focus, our estimates are strikingly similar to the averages in that survey. Calculations based on it indicate that workers spend 0.055 of work time in non-work, slightly less than in the ATUS, and similar fractions in both surveys report no time spent not working at the workplace.

Divergences in educational attainment are an obvious first explanation of dissimilarities between minority and majority workers. If we divide the sample into those with at least a college education and those without a college education, and then among African Americans, non-black Hispanics, and other races, the fraction of time spent at the workplace not working exceeds that of majority workers with the same educational attainment. The additional non-work time by minorities is roughly the same for both college- and less-educated workers. Only among less-educated Asian American men and more-educated Asian American women is the fraction (very slightly) below that among comparable non-Hispanic whites.

A notable feature in these statistics is that η is nearly identical for non-Hispanic white men and women. Workers of each gender spend approximately 6.5% of time at the workplace not working—about a half-hour in a full workday. These fractions may seem low, but time spent eating during work hours is usually not at the workplace and is thus not included in the numerator or denominator of these fractions. Among minority groups there is no obvious general pattern of differences between male and female workers—African American, non-black Hispanic, and men of other races spend greater fractions of their time in non-work activities at their worksites than do their female counterparts, whereas Asian American male workers spend less.

One might be concerned that the samples are unrepresentative in various ways, perhaps because of the exclusion restrictions that we have used in creating this sub-sample. This concern should be allayed, at least for male workers, by comparisons within columns of the fourth and fifth rows in the upper half of Table 1. The weighted fractions of male workers in each of the five racial/ethnic groups in the ATUS are very near those reported in the ACS averaged from 2003 to 2012 (Ruggles et al. 2015). The differences between female workers' representation in our ATUS sub-sample and the ACS are proportionately larger than the differences among men, but they are small among the three largest racial/ethnic groups.

Accounting for Other Demographic, Industry, and Occupational Influences

Adjusting for Worker and Job Characteristics

The patterns of raw differences shown in the top rows of each half of Table 1, and the implied absence of any overall difference by gender, are interesting but not conclusive. They could stem from differences in 1) the amount of time spent at the workplace or the number of hours usually worked, 2) labor supply due to family circumstances, 3) location or the state of the aggregate labor market, 4) the day of the week or month of the year for which the time-diary is completed, or 5) occupation/industry attachment. We estimate OLS regressions describing η to account for these factors by adding increasingly large numbers of vectors of covariates. We use non-Hispanic whites within each gender as the comparison group, and examine how the addition of these covariates alters our conclusions about racial/ethnic relative differences in non-work time at the workplace.

The first rows in the top and bottom parts of Table 2 present the differences in η between workers in each of the four racial/ethnic minorities and that of non-Hispanic whites, simply reproducing the differences implicit in Table 1, plus their standard errors. They thus estimate α_1 in a version of Equation (1) that excludes the vector of covariates Z. The equation is:

$$\eta_{ist} = \alpha_0 + \alpha_1 X_{ist} + \alpha_2 Z_{ist} + \varepsilon_{ist}, \qquad (1)$$

where i is an individual, s is a state, t is a month/year, X is the vector of indicators of race/ethnicity, the α_j are parameters to be estimated, and ε is the disturbance term. What is most intriguing in these raw differences is that all four are positive—all minorities identifiable in the CPS, including those who may not be viewed as disadvantaged, spend greater fractions of their time at their workplace not working compared to non-Hispanic whites. These differences are largest, and statistically greater than zero, for the two largest minority groups: African Americans and non-black Hispanics.

In the second rows of each half of Table 2, we add pairs of quadratic terms in the length of the respondent's usual workweek, as recalled, and the time spent at the workplace on the diary day, as recorded in the diary. Because race and ethnicity are correlated with such demographic differences as marital status, age and number of children, geography, and other indicators, the differentials in the first rows of Table 2 may merely reflect familial and other incentives that alter the amount of non-work at the worksite. To account for this possibility, the second rows also include as covariates: marital and geographic status, a quadratic in potential experience, vectors of five indicators of the ages of the children in the household, and four indicators of educational attainment. We also add a vector of indicators of state of residence, given geographic differences in the racial/ethnic distributions of the US work force. Finally, the second equations in Table 2 also include the year of the survey (perhaps accounting for the cyclical variation in non-work time at work demonstrated by Burda et al. 2020), month of the year, and day of the week for which the respondent's time-diary was recorded.

Except for Asian American men, the inclusion of all these covariates changes the estimated differential in reported non-work time between minority groups and majority workers by less than one standard error, with four of the eight re-specifications showing a greater racial/ethnic differential. Moreover, the changes are small in absolute terms. The differences remain statistically significant for both women and men in the two largest groups, however, and they become statistically significant among Asian American men. The greater propensity for workplace non-work noted in Table 1 is not due to differences in work time or demographic characteristics of minority and majority workers.

Table 2. Parameter Estimates, Racial/Ethnic Effects on the Fraction of Work Time Not Working, ATUS Employees, 2003–2012 (Base Group Is Non-Hispanic Whites)

	African American	*Non-black Hispanic*	*Asian American*	*Other races*	
		Men (N = 17,777)			$\bar{R}^2$
Raw differential	0.0148	0.0203	0.0034	0.0056	0.005
	(0.0036)	(0.0031)	(0.0036)	(0.0059)	
Add hours, demographic and geographic indicators[a]	0.0120	0.0198	0.0091	0.0078	0.079
	(0.0036)	(0.0034)	(0.0039)	(0.0062)	
Add union and detailed industry and occupation indicators[b]	0.0076	0.0151	0.0082	0.0027	0.112
	(0.0031)	(0.0029)	(0.0047)	(0.0060)	
		Women (N = 17,771)			
Raw differential	0.0112	0.0132	0.0078	0.0025	0.002
	(0.0027)	(0.0034)	(0.0057)	(0.0063)	
Add hours, demographic and geographic indicators[a]	0.0113	0.0093	0.0091	–0.0037	0.085
	(0.0030)	(0.0039)	(0.0062)	(0.0066)	
Add union and detailed industry and occupation indicators[b]	0.0085	0.0067	0.0058	–0.0044	0.112
	(0.0028)	(0.0032)	(0.0048)	(0.0062)	

Notes: Standard errors of parameter estimates in parentheses. ATUS, American Time Use Survey.
[a]Quadratics in daily work time, usual weekly hours, and potential experience; vectors of indicators of education, of age of youngest child, of states, of years, of months, and of days of the week; indicators of marital and metro status.
[b]Indicators for 513 occupations, 259 industries, and union membership.

The estimates thus far do not consider the possibility that the structure of work by race/ethnicity might differ across industries and occupations. To account for this potential confounder we re-estimate the equations, adding vectors of indicators accounting for over 500 occupations and over 250 industries (i.e., the greatest detail provided by the ATUS), and also for union coverage. The results of making these additions are presented in the bottom rows of the two parts of Table 2. Among African American and non-black Hispanic men, including these very fine occupation/industry indicators does produce a one-fourth to one-third reduction in the estimated minority-majority differentials in η. Those differentials that had been significantly positive, however, remain so. Among women workers, including these additional covariates also reduces the estimated racial/ethnic differentials, again by one-fourth to a bit over one-third.

If we re-estimate these final equations while removing the time spent eating at the workplace, the racial-ethnic differentials for male workers are proportionately even larger; those for female workers are approximately the same relative size. If we include both the quadratic in time at the workplace from the time diaries and the total time reported in the diaries as working, the adjusted demographic differences are essentially unchanged. While all of the estimates reported in the tables and discussed in the text use the proportions of time at work spent not working, using the raw amounts of non-work time instead yields slightly larger and more statistically significant racial/ethnic differentials. Still another possibility is that our estimates include the slightly less than 2% of workers who report spending at least 50% of their time on the job on non-work. Excluding these respondents from the estimates does not qualitatively change the results.

While this vast array of additional controls leaves the estimated differentials for the two largest groups positive and statistically significant, their declines are interesting, as are the sources of these declines—among the occupation indicators, the industry indicators, and union status. To examine what factors are most closely associated with the reduction in the estimates, we implement Gelbach's (2016) order-invariant decomposition to examine the sources of the changes in the adjusted estimates of η between the second and third rows of each half of the table. Appendix Table A.1 presents the results of these decompositions. No single factor—occupational attachment, industry of employment or union status—consistently accounts for the generally less-positive impacts of race/ethnicity shown in the changes between the second and third rows of each part of Table 2.

The descriptive statistics in Table 1 allowed comparisons by racial/ethnic group of gender differences in work site non-work. They did not, however, account for variations that might arise from any gender disparities in the large sets of controls that we added to generate the estimates in most of Table 2. To obtain an adjusted gender difference in on-the-job non-work, we re-estimate the equation in the last rows of Table 2 overall, based on the 35,548 workers in the sample. All other things being equal, male workers spend an additional fraction of 0.001 (s.e. = 0.002) of their time at the work site not working compared to female workers. The conclusion of few gender dissimilarities conveyed by the raw differences in Table 1 is supported even after accounting for large numbers of possible covariates. While significant racial/ethnic differentials in non-work at the workplace do exist, essentially no disparities emerge between otherwise identical male and female employees.

Robustness—Supply Side Effects

Since the estimated effects result from interactions between workers and employers, identifying supply-and-demand effects separately is generally impossible. Nonetheless, certain characteristics of workers and their workplaces can be more readily linked to supply behavior (demographic variations) or demand behavior (differences in the organization of work). We first consider the divergence in non-work by educational attainment by dividing the sample into workers with at least a college degree and those without. To examine whether the racial/ethnic differences in non-work pervade the educational distribution, we re-estimate the fully specified models presented in the bottom rows of Table 2 separately over the two groups of workers as distinguished by their educational attainment.

Table 3. Supply-Side Robustness Checks, Excess of Non-Work Time over Non-Hispanic Whites among African Americans and Non-Black Hispanics, ATUS Employees, 2003–2012

African American	*Non-black Hispanic*	*N*	$\bar{R}^2$	*African American*	*Non-black Hispanic*	*N*	$\bar{R}^2$
			Men				
	College graduates				Less than B.A.		
0.0067	0.0111	6,317	0.091	0.0060	0.0156	11,460	0.131
(0.0077)	(0.0066)			(0.0046)	(0.0040)		
	Excellent or very good health[a]				Good to poor health[a]		
0.0012	0.0110	4,869	0.121	0.0106	0.0236	3,234	0.192
(0.0064)	(0.0070)			(0.0095)	(0.0080)		
	Veteran				Non-veteran		
–0.0169	0.0009	2,506	0.209	0.0106	0.0162	15,271	0.116
(0.0091)	(0.0116)			(0.0043)	(0.0035)		
			Women				
	College graduates				Less than B.A.		
0.0073	0.0160	6,277	0.080	0.0078	0.0055	11,494	0.131
(0.0043)	(0.0065)			(0.0042)	(0.0051)		
	Excellent or very good health[a]				Good to poor health[a]		
0.0027	0.0196	4,784	0.133	0.0083	0.0068	3,346	0.156
(0.0066)	(0.0115)			(0.0072)	(0.0090)		

Notes: Standard errors in parentheses. The equations include all the controls used in the final equation presented in Table 2 plus indicators for Asian Americans and members of other races. ATUS, American Time Use Survey; B.A., bachelor's degree.
[a]Includes only observations for 2006 to 2008 and 2010 to 2011, since information on health was only collected in those years.

The results of this disaggregation are shown in the first rows of the upper and lower panels of Table 3. We list only the estimated coefficients for African Americans and non-black Hispanics, as the reduced sizes of the subsamples of Asian Americans and members of other races render probability statements about their differences from majority workers useless. (Indicators for these other groups are included in the estimates but are not reported in the table.) The first two columns present the results for college graduates; the second two columns, those for workers without a college degree. Comparing results in columns (1) and (3) for African Americans, or (2) and (4) for non-black Hispanics, we find remarkably small differences by educational attainment except for non-black Hispanic women. For example, the excess workplace non-work by African Americans over non-Hispanic whites among college graduates is 0.0068; among non-graduates, 0.0066. The results in Table 2 are not caused by variations in behavior generated by differences in educational attainment.[3]

The estimates in Table 2 did not account for the possibility that health limitations might restrict the fraction of work time spent working at the

[3]The influence of age on non-work time may differ between majority and minority workers. To examine this, we created an indicator, age $\leq$ 40, which divided the samples essentially in halves. Including this indicator and its interactions in the final equations shown in Table 2, we found no difference in the racial/ethnic non-work differentials by age.

worksite, and these might differ by race/ethnicity. The ATUS did not collect information on respondents' health for some years in the sample period. For those five years in which such data are available—2006 to 2008 and 2010 to 2011—we divide the samples: slightly more than half of the sample reported being in excellent or very good health, and slightly less than half indicated being in less than very good health. Our measure is a subjective (self-)assessment of the person's health. Nonetheless, other evidence (Bound 1991) has suggested that such measures generally accord on average with objective health characteristics. Whether this approximation holds for all racial/ethnic and gender groups is not clear, although some research findings (Dowd and Todd 2011) have demonstrated racial/ethnic differences in responses to subjective questions about health status. The estimates of the final equations in Table 2 for these two sub-samples are presented in the second rows of Table 3.

Comparing between columns (1) and (3), and (2) and (4), we see that—especially for minority men and African American women—racial/ethnic differences in non-work time at the workplace arise mainly among workers who are not in at least very good health. The opposite result is seen for non-black Hispanic women. In these data, 64% of white non-Hispanic employees report being in at least very good health compared to only 50% of African American employees. Clearly, some of the differences shown in Table 2 arise from the worse average health of African Americans.

The samples of military veterans among women in the ATUS are so small as to prevent disaggregating the samples of women by veteran status. Among men in these samples, however, 17% of African Americans are military veterans, as are 14% of non-Hispanic whites and 4% of non-black Hispanic males. Perhaps military service alters behavior in the workplace, or self-selection into the military is related to some characteristic that also causes different subsequent behavior in non-military employment. To examine this possibility, we re-estimate the most expanded equations separately for sub-samples of military veterans and non-veterans; these results are presented in the bottom row of the upper panel of Table 3. Among African American male veterans, non-work at work is not statistically different from that of the average non-Hispanic white male veteran. Similarly absent is any significant difference between non-black Hispanic male veterans and majority veterans. With regard to reported time spent not working at the workplace, all of the variation among non-Hispanic whites, African Americans, and non-black Hispanics stems from the non-veteran status of the majority of minority workers.

Robustness—Demand Side Effects

Several institutional differences among the sample observations might account for, or at least minimize, the findings implied in the bottom rows of the panels in Table 2. The roughly one-sixth of workers in the public sector might be less stringently monitored, and public-sector jobs might provide more protection for minority workers against employer discrimination. As in the previous sub-section, we thus form separate sub-samples of public and private employees.

Using the same format as in Table 3, we present the results of re-estimating the fully specified equation describing non-work at the workplace on these two sub-samples in the first rows of Table 4. Among men, the racial/ethnic differences are greater in the private than in the public sector; among women the opposite is true. Since the much larger private sector drives the results in Table 2, and since the racial/ethnic differences there were larger among men, our results suggest that this source of possible variation in the structure of monitoring does not produce the basic results.

About half of the American workforce is paid hourly. It is possible that hourly workers are monitored more closely than others, especially because few salaried workers are currently subject to the provisions of the Fair Labor Standards Act (Brown and Hamermesh 2019, table 2). This might account for the racial/ethnic differentials in non-work at the worksite demonstrated in this section. To examine this possibility, we created sub-samples of hourly paid and salaried workers and re-estimated the expanded equations from Table 2 over the two sub-samples. We show the results in the second row of the Men panel and of the Women panel of Table 4. Except among African American men, the excess of non-work over non-Hispanic whites is greater among salaried than among hourly paid employees. All the racial/ethnic differences remain positive, indicating that the results overall do not support the importance of differential monitoring by method of payment.[4]

Although the decompositions in the previous section on Adjusting for Worker and Job Characteristics show that union status did not account for changes in the estimates, the demonstrated interest of trade unions in minority employees might lead to different behavior in the union and non-union sectors. Trade unions may provide more services to minority workers, perhaps for political reasons (at least to African American workers, who are more heavily unionized than other groups) or the preferences of union members and leaders to protect minority workers. To examine this possibility, we create sub-samples of unionized and non-unionized workers and re-estimate the expanded equations. Among men, the racial/ethnic differences are larger in the (much larger) non-union sector; among women the opposite is true. But all the differences remain positive, suggesting that whether a workplace is unionized is not generating the basic results.

[4]A related cut of the data divides the sample into blue- and white-collar workers. Not surprisingly, re-estimating the expanded equation over these sub-samples yields results on the minority-majority differences that are qualitatively the same as those shown in Table 4.

Table 4. Demand-Side Robustness Checks, Excess of Non-Work Time over Non-Hispanic Whites among African Americans and Non-Black Hispanics, ATUS Employees, 2003–2012

African American	*Non-black Hispanic*	*N*	$\bar{R}^2$	*African American*	*Non-black Hispanic*	*N*	$\bar{R}^2$
			Men				
	Public employees				Private employees		
0.0024	0.0124	2,687	0.234	0.0075	0.0154	15,090	0.109
(0.0085)	(0.1200)			(0.0042)	(0.0035)		
	Hourly				Salaried		
0.0080	0.0137	9,609	0.128	0.0023	0.0147	8,168	0.123
(0.0049)	(0.0049)			(0.0058)	(0.0056)		
	Union member or covered				Non-union		
0.0025	0.0110	2,721	0.190	0.0099	0.0155	15,056	0.111
(0.0095)	(0.0123)			(0.0042)	(0.0035)		
			Women				
	Public employees				Private employees		
0.0165	0.0333	3,553	0.101	0.0066	0.0025	14,218	0.122
(0.0059)	(0.0117)			(0.0037)	(0.0043)		
	Hourly				Salaried		
0.0057	0.0023	10,941	0.135	0.0123	0.0084	6,830	0.118
(0.0042)	(0.0055)			(0.0046)	(0.0056)		
	Union member or covered				Non-union		
0.0179	0.0139	2,245	0.275	0.0069	0.0060	15,526	0.113
(0.0086)	(0.0171)			(0.0344)	(0.0040)		

Notes: Standard errors in parentheses. The equations include all the controls used in the final equation presented in Table 2 plus indicators for Asian Americans and members of other races. ATUS, American Time Use Survey.

Possible Explanations

Aggregating the adjusted effects among men, based on the results in the preceding section, the best estimate is that on average minority male workers (using a sample-weighted average of the parameter estimates in the bottom row of the top half of Table 2) spend an additional 1.10% of each workday not working on the job compared to their majority counterparts. Over a 250-day full-time work year this amounts to an additional 22 hours per year of not working while at the workplace. Taking all four female minority groups together, the weighted average of the estimates suggests that the average minority female worker spends 0.64% less of each workday actually working at the worksite compared to her majority counterpart (i.e., 14 hours of a full-time work year).[5] From the sections titled Robustness—

[5]One might argue that the differences we have identified arise because of racial/ethnic differences in time use away from the job. Minorities might spend more time commuting, might sleep less, or might engage in more household production. These measures may well be endogenous with non-work time at work. Nonetheless, to examine their relation to the racial/ethnic differences that we have focused on, we include each separately in the expanded equations shown in the bottom of each panel of Table 2, and then include them jointly. Including each separately actually raises slightly the estimated excess of minority over majority non-work time. Taking them together, their inclusion raises the excess among men by approximately 10%; among women, by approximately 15%.

Supply Side Effects and Robustness—Demand Side Effects, evidence indicates that except for the possible role of differences in health between African American and majority workers, a large number of possible supply- and demand-side differences fail to account for the general results.

Perhaps the differentials are attributable to a greater willingness of minorities to report non-work time on the job or racial/ethnic differences in views about what constitutes work time. If differences between minority groups and the majority workers are causing reporting differences, one would expect that they would be greater among immigrant minority workers, who have yet to assimilate the behavior of the majority. To consider this possibility, we divided the sample into native and immigrant employees and re-estimated the expanded equation describing non-work time at the workplace. Because the sub-samples become quite small, we relegate the results to Appendix Table A.2. Among immigrants, the difference between African Americans and non-Hispanic whites exceeds that among natives. But among non-black Hispanics, who account for nearly half of all immigrants in the sample, the excess non-work over whites at the worksite is about the same as it is among natives. Perhaps most important, the additional non-work time among natives for the two largest minority groups differs little from that in the entire sample. Nativity as a source of differences generating this outcome may be important, but it cannot account for our central finding.

Our findings also do not stem from minorities' greater willingness to report different activities, including non-work at the workplace. Non-Hispanic whites report engaging in 19.78 (s.e. = 0.032) separate activities per day on average, while the average numbers of those reported by minorities are: African Americans, 18.77 (s.e. = 0.078); non-black Hispanics, 18.05 (s.e. = 0.071); Asian Americans, 18.90 (s.e. = 0.134); and other races, 19.63 (s.e. = 0.188). Minorities report fewer, not more, activities per day than otherwise-identical majority workers.

Some additional evidence that these results do not merely arise from racial differences in the willingness to report non-work comes from analyses of the General Social Survey's (GSS's) questions eliciting attitudes on the social desirability of work. The GSS includes two questions that allow us to examine such differences: 1) For all respondents, "If you were to get enough money to live as comfortably as you would like for the rest of your life, would you continue to work or would you stop working?" and 2) For workers, do you agree with the statement, "My main satisfaction in life comes from work." Estimating a probit (ordered probit) on the responses to Question 1 (and 2) and excluding racial groups other than whites and African Americans because of lack of information, the latter are insignificantly more likely to say they would stop work. They are also, however, nearly significantly more likely to agree or agree strongly with the statement about the importance of satisfaction with work. The results, presented in Appendix Table A.3, show no clear racial differences in how people view the desirability of work, lending no support to the idea that variations in willingness to report non-work at work account for our results.

We should note that although we have held constant for remarkably detailed industry and occupation characteristics, even within those narrow cells minorities may be assigned to tasks that are inherently more strenuous and require more "downtime." Clearly, with these data we cannot investigate this explanation. Alternatively, and consistent with older, loosely related indirect evidence (Hellerstein, Neumark, and Troske 1999), extra non-work time at the workplace reported by minority employees might enable them to be more productive than majority employees during the (lesser) amount of time per hour on the job when they are actually working.

Minorities may spend more workplace time not working if discriminatory practices lower the returns to work time—especially regarding promotion and long-term career prospects—and thus the long-term penalties for non-work. Comparing self-employed minority to their majority counterparts provides a weak test of this explanation. Since self-employed workers cannot be promoted, if employer discrimination in promotion probabilities explains our results, we would not expect racial/ethnic differences among the self-employed. Reported non-work time at the worksite by the minority self-employed might, however, exceed that of majority self-employed workers if customer discrimination reduces the gains from marginal increases in work time.

Table 5 shows the mean non-work time of majority and minority self-employed workers by gender. Among minority self-employed workers the means are lower than those among minority employees shown in Table 1, but the same is true of the majority self-employed workers and employees. Indeed, the double-differences in the means (minority–majority, self-employed–employees) are small and positive among men and African American women. Given the small samples of self-employed workers, none is statistically different from zero.

Re-estimating the equations at the bottom of the two panels of Table 2 for self-employed male and female workers yields the same conclusion: The additional non-work time at the worksite of minority workers is the same among the self-employed as among employed workers in these samples. The point estimates of the double-differences, although not statistically significant because of the relatively small samples of self-employed minority workers, suggest no difference in the relative amounts of non-work at the workplace. This weak test rejects the possibility that responses to discriminatory promotion practices are generating our results. These may still exist, but their impact is indistinguishable from those attributable to customer discrimination against the self-employed.

Perhaps minority employees report more non-work time per hour at the workplace because their lives are more stressful, and the increased reported

Table 5. Mean Fraction Non-Work at Work, and Parameter Estimates of Minority Effects on This Fraction, ATUS Self-Employed Workers, 2003–2012

	Non-Hispanic white	*African American*	*Non-black Hispanic*	*Asian American*	*Other races*	$\bar{R}^2$
			Men (N = 2,342)			
Average fraction non-work	0.0472	0.0532	0.0587	0.0481	0.0328	
	(0.0030)	(0.0111)	(0.0073)	(0.0066)	(0.0087)	
Differential over Non-Hispanic whites[a]		0.0166	0.0082	0.0284	0.0057	0.154
		(0.0265)	(0.0115)	(0.0127)	(0.0183)	
			Women (N = 1,005)			
Average fraction non-work	0.0531	0.0724	0.0427	0.0284	0.1349	
	(0.0048)	(0.0191)	(0.0101)	(0.0080)	(0.0743)	
Differential over Non-Hispanic whites[a]		0.0107	0.0001	–0.0270	0.1327	0.211
		(0.0199)	(0.0157)	(0.0239)	(0.1117)	

Notes: Standard errors of means in parentheses below the raw averages, and standard errors of estimates below the parameter estimates. ATUS, American Time Use Survey.
[a]The equations include all the controls in the final equation presented in Table 2.

non-work compensates for their extra stress. We can examine this possibility using two data sets. First, in 2003 the Panel Study of Income Dynamics (PSID) included a question asking one respondent per household, "How often do you feel rushed or pressed for time? Almost always; often; sometimes; rarely; never" (see Hamermesh and Lee 2007). Other things being equal, African American men are less likely to indicate that they are almost always or often stressed for time than are other men, but the difference between them and whites is not quite statistically significant. African American women are significantly less likely to feel stressed for time than otherwise identical non-Hispanic white women.

Second, in 2010 and 2012 the ATUS asked respondents to indicate at three randomly chosen times of the diary day how stressed they were while performing a particular activity, with responses ranging from 0, indicating not stressed, to 6, indicating very stressed. We estimate activity-level ordered probits over this measure. The estimates suggest that, all else being equal, African Americans are significantly less likely to feel stressed during randomly selected activities than other groups. The differences for non-black Hispanics and Asian Americans are small and negative, with t-statistics below 1, whereas those for other races are positive and nearly significant statistically. These results from the PSID and the ATUS counter the notion that lesser non-work at the workplace reported by minorities is a response to general feelings of stress (see Appendix Table A.4 for further discussion).

Our results cannot be explained by an array of behavioral differences that might arise from readily measurable incentives generated by labor-market discrimination. Instead, they may be attributable to more subtle impacts of discrimination, which are not testable on these data. The findings also might arise from more basic differences, which in turn could well result from a long history of discrimination. In the end, the best conclusion is that racial/ethnic differences in non-work time at the workplace are real. We have ruled out a variety of explanations for them, but discerning their ultimate cause(s) requires substantial additional work that is beyond the scope of any of the data used here.

Economic Significance of Racial/Ethnic Differences in Non-Work at the Workplace

Although statistically significant and robustly so, these estimates of racial/ethnic differences are not large. How do they alter our conclusions about the extent of racial/ethnic differences in outcomes, particularly in hourly earnings—the best measure of the price of labor of different races/ethnicities? On this issue, a recent study (Ananat, Fu, and Ross 2018) estimated adjusted black–white wage differentials at approximately 14%, adjusted Hispanic and non-Hispanic white wage differentials at approximately 15%, adjusted Asian American wage differences at approximately 13%, and adjusted white–other races differences at approximately 14%. Using samples from the National Longitudinal Survey of Youth (NLSY) 1979 and the NLSY 1997, D'Haultfoeuille, Maurel, and Zhang (2018) found median estimates of the African American–white wage gap of approximately 12%.

While indicative, neither of these studies can account for the vast vectors of covariates that might affect earnings and that are available in the ATUS and its parent, CPS. To measure racial/ethnic earnings differentials using the same specifications summarized in Table 2, to avoid estimating them over the samples used there (since all of the workers in the ATUS in 2003 to 2012 were in the CPS in those years), and to use larger samples, we specify log-earnings equations using the CPS-MORG for 2014 to 2016. Estimates of the racial/ethnic effects on log-earnings for men and women are presented in Table 6. The parameter estimates shown in the first row of each panel are based on equations containing all the demographic, work time, and other indicators used in Table 2 (except, of course, reported work time in a time-diary). The second set of estimates, shown in the third row of each panel, adds union status and the vectors of very detailed occupation/industry affiliations, as did the final estimates in Table 2.

For the two largest minority groups the results in Table 6 make sense: 1) earnings differentials are smaller for women than for men, and 2) including vectors of occupation/industry indicators reduces the measured differentials for these groups by one-third to one-half. These earnings differentials measure:

$$D = \ln(E/H)_m - \ln(E/H)_w < 0, \tag{2}$$

Table 6. Parameter Estimates, Racial/Ethnic Effects on ln(Weekly Earnings), CPS Employees, 2014–2016, and Adjustments for Differential Non-Work at the Workplace (Base Group Is Non-Hispanic Whites)

	African American	*Non-black Hispanic*	*Asian American*	*Other races*	$\bar{R}^2$
		Men (N = 187,242)			
[a]Adjusted earnings differential	–0.171	–0.157	–0.083	–0.054	0.614
(from CPS regression) (D)	(0.004)	(0.003)	(0.007)	(0.010)	
Accounting for non-work (D')	–0.159	–0.137	–0.074	–0.046	
[b]Adjusted earnings differential	–0.104	–0.093	–0.053	–0.033	0.670
(from CPS regression) (D)	(0.004)	(0.004)	(0.007)	(0.009)	
Accounting for non-work (D')	–0.096	–0.078	–0.045	–0.030	
		Women (N = 173,739)			
[a]Adjusted earnings differential	–0.109	–0.122	–0.056	–0.042	0.656
(from CPS regression) (D)	(0.004)	(0.004)	(0.007)	(0.010)	
Accounting for non-work (D')	–0.098	–0.113	–0.047	–0.046	
[b]Adjusted earnings differential	–0.057	–0.061	–0.028	–0.024	0.711
(from CPS regression) (D)	(0.004)	(0.004)	(0.006)	(0.009)	
Accounting for non-work (D')	–0.048	–0.054	–0.022	–0.028	

Notes: Standard errors of parameter estimates in parentheses. CPS, Current Population Survey.
[a]Quadratics in usual weekly hours, and potential experience; vectors of education indicators, of age of youngest child, of states, of years and of months, and indicators of marital and metro status.
[b]Adds indicators for 513 occupations, 259 industries, and union membership.

where E is weekly earnings, H is usual weekly hours as reported, m is minority, and w is majority.[6]

Adjusting the earnings differentials to reflect racial/ethnic differences in reported non-work time at the workplace means replacing H_m for minorities by $H_m[1\text{-}x_m]$, and H_w for non-Hispanic whites by $H_w[1\text{-}x_w]$, where x is the fraction of reported non-work time at the workplace. This substitution yields adjusted wage differentials of:

$$D' = D - [x_w - x_m], \tag{3}$$

noting that ln(1-x) is approximately –x, where the estimated x_m in Equation (3) are based on the parameter estimates in Table 2 (with a base of $x_w = 0$ for the majority, as is implicit in Table 2, $D' = D + x_m$).

Directly below each estimate of D, and for each of the two specifications, Table 6 lists D', the adjusted CPS earnings differential further adjusted for the estimated racial/ethnic differences in reported non-work time at the workplace shown in Table 2. Using our estimates for men, and adjusting

[6]Some of the wage differentials may reflect the possibility that earnings as measured already account for differences in non-work at work. We cannot identify this compensating differential. We can, however, estimate reduced-form equations based only on non-Hispanic whites in the ATUS, relating log-earnings to the broadest set of covariates included in Table 2, and an indicator of whether the worker reports any on-the-job non-work. Those who report some non-work, averaging 10% of the workday, receive 2% lower wages, other things being equal. Thus, only part of non-work time results in a wage penalty. This suggests—but does not prove (because of the identification problem)—that it is correct to adjust observed racial/ethnic earnings differentials for differences on non-work time.

reported hours worked for racial/ethnic differences in on-the-job non-work, the measured wage disadvantage of African American men is reduced by nearly 1 percentage point (about a 10% reduction), and among African American women by more than one-half of a percentage point.

These effects are modest in magnitude and smaller than well-known racial/ethnic differences in earnings/capita attributed to racial/ethnic differences in employment rates and hours per worker. But in comparison, the effects are no smaller than the adjustments/explanations that have been produced in studies that have examined the impacts of unusual determinants of demographic differences on wages (e.g., Gielen, Holmes, and Myers 2016). They suggest some revisions in thinking about the racial/ethnic wage differentials that have received so much attention from social scientists.

Conclusions

We have demonstrated that minorities in the United States—African Americans, non-black Hispanics, Asian Americans, and others—on average report spending larger fractions of their time at their workplaces engaged in non-work activities than do majority workers. These differences are robust to the inclusion of large numbers of demographic variables, measures of work time, and even extremely detailed indicators of industry and occupational attachment. They are large enough to suggest some modifications of our notions of the magnitudes of racial/ethnic differences in pay per hour of actual work time, leading perhaps to reductions of 10% in the estimated earnings disadvantage of African American and non-black Hispanic men.

We have rejected some explanations for the differences in non-work time at work based on incentives facing minorities. Similarly, the dissimilarities are not explained by variations in the amounts and kinds of activities undertaken outside the workplace. Rather, they are consistent with workers' responses to discrimination in wage-setting, or with other more basic differences whose ultimate cause could also be discrimination.

The ATUS is the only nationally representative data set of which we are aware that provides information on what large samples of workers are doing at their workplaces. This uniqueness is unfortunate. The questions that might be answered with more such data go well beyond pointing out demographic differences in how time at work is spent, although these are important for such labor-market outcomes as worker productivity and wage differentials. Expanded information on time use at work would enable much deeper study of the temporal dynamics of worker productivity, allowing the scientific management studies of the post–World War I era (e.g., Florence 1924) to be considered on a more general and broadly applicable basis.

Appendix

Table A.1. Decomposition of Changes in Parameter Estimates in Table 2

	Change due to:				
	Occupations	*Industries*	*Union status*	*Residual*	*Total change*
Parameter on:		**Men**			
African American	0.0009	–0.0020	–0.0005	–0.0028	–0.0044
Non-black Hispanic	0.0122	–0.0003	0.0003	–0.0169	–0.0047
Asian American	–0.0144	0.0010	0.0006	0.0119	–0.0009
Other races	0.0033	–0.0030	–0.0003	–0.0052	–0.0052
		Women			
African American	–0.0013	–0.0009	–0.0006	0.0000	–0.0028
Non-black Hispanic	0.0059	0.0001	0.0001	–0.0087	–0.0026
Asian American	–0.0024	–0.0007	0.0006	–0.0008	–0.0033
Other races	0.0012	0.0007	0.0002	–0.0028	–0.0007

Notes: Change between the second and third sets of estimates in Table 2.

Table A.2. Parameter Estimates, Native and Immigrant Sub-Samples (Racial/ Ethnic Effects with Non-Hispanic Whites as the Base Group)

	African American	*Non-black Hispanic*	*Asian American*	*Other races*	*N*	$\bar{R}^2$
		Men				
Natives	0.0042	0.0181	0.0032	0.0069	14,633	0.122
	(0.0041)	(0.0057)	(0.0115)	(0.0075)		
Immigrants	0.0253	0.0105	0.0004	–0.0133	3,144	0.139
	(0.0111)	(0.0070)	(0.0070)	(0.0112)		
		Women				
Natives	0.0008	0.0073	–0.0055	–0.0037	15,273	0.121
	(0.0034)	(0.0058)	(0.0089)	(0.0082)		
Immigrants	0.0132	0.0102	0.0174	–0.0117	2,498	0.192
	(0.0095)	(0.0953)	(0.0110)	(0.0123)		

Notes: Standard errors in parentheses below the parameter estimates here and in Appendix Tables A.3 and A.4. The equations include all the controls used in the final equation presented in Table 2.

Table A.3. Racial Effects on Attitudes toward Work (Parameter Estimates on Indicator for African Americans), GSS Various Waves

Dependent variable:	
Would continue to work if rich[a]	–0.0223
	(0.0345)
$N = 15{,}863$	
Work is main source of satisfaction[b]	0.1168
	(0.0693)
$N = 2{,}699$	

Notes: GSS, General Social Survey.

[a]Probit estimates based on data from 1973, 1974, 1976, 1977, 1980, 1982, 1984, 1985, 1987 to 1991, 1993, and even-numbered years from 1994 to 2010. A quadratic in age, years of schooling, own income, and indicators of gender, and the year of the survey are included, and the estimation uses sampling weights.

[b]Ordered probit estimates based on data from 2002 and 2006. A quadratic in age, years of schooling, own income, and indicators of gender and the year of the survey are included, and the estimation uses sampling weights.

Table A.4. Parameter Estimates, Racial/Ethnic Effects on Stress (with Non-Hispanic Whites as the Base Group)

Data set and Dependent variable:	*African American*			
	Men	**Women**		
PSID 2003, Married[a]	–0.0597	–0.1039		
Probit on indicator always/often stressed	(0.0354)	(0.0271)		
N =	1,649	2,189		
	African American	*Non-black Hispanic*	*Asian American*	*Other races*
		All		
ATUS 2010, 2012[b]				
Ordered probit, stressed during activity, 6 to 0 scale	–0.2447	–0.0037	–0.0132	0.1574
	(0.0513)	(0.0436)	(0.1288)	(0.0847)
N = 40,817				

Notes: ATUS, American Time Use Survey; PSID, Panel Study of Income Dynamics.
[a]Includes each spouse's earnings, hours of work and health status, and family income, and the ages and number of children.
[b]Includes all respondents who answered these questions in 2010 and 2012. The specification contains the same controls as the equations reported in the third rows of Table 2, a vector of the 18 major categories of time use indicating time spent on each major activity during the diary day, plus an indicator of gender and its interaction with marital status. Standard errors are clustered on the individual respondents.

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