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## **RACIAL/ETHNIC DIFFERENCES IN NON-WORK AT WORK**

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## **ABSTRACT**

Evidence from the American Time Use Survey 2003-12 suggests the existence of small but statistically significant racial/ethnic differences in time spent not working at the workplace. Minority employees, especially men, spend a greater fraction of their workdays there not working than do Non-Hispanic whites. These raw time differences are robust to the inclusion of large numbers of demographic, time and geographic controls, being reduced by an average of about one-third even when very detailed industry and occupation controls are accounted for. Most do not vary by union status, public-private sector attachment, pay method, educational attainment or health status. The estimates imply that accounting for the differences in non-work while at the worksite may explain up to 10 percent of the adjusted wage gap between minority workers and Non-Hispanic white workers.

## I. Hours on the Job and Hours Working

Commonly used statistics on labor productivity and real wages are normally 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 either reported weekly hours in the monthly household-based Current Population Survey (CPS), weekly, monthly or annual hours in other household surveys, or weekly hours reported by employers in the monthly Current Employment Statistics (CES).

The 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 *et al.*, 2013 and 2019), measures of growth in living standards per hour of work, and demographic wage differentials in cross sections. If, for example, hours reported worked by minority or female workers exceed actual hours by less than 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 *et al.*, 2005), the first to do so, provides diary information on over 400 possible activities engaged in by large samples of (recent CPS) respondents, including detailed information on a wide variety of different activities undertaken at the workplace. We use these data from 2003-12 to study differences among demographic groups in the fraction of time that they spend at the workplace but not working (Hofferth *et al.*, 2015).

We examine a large variety of explanations for this general difference, examining how much it is reduced by controlling for the usual demographic differences and for wide arrays of industry and occupation indicators. Finding that these reduce the racial/ethnic differences but by at most one-third, we then examine whether they arise from differences in reporting behavior. We then calculate how much measured adjusted

wage differentials change when we make further adjustments for racial/ethnic differences in hours reported working at the workplace.

Of course, there are very well known racial/ethnic differences in employment/population ratios and weekly work hours in the U.S. For African-American men, for example, these differences imply that 13 percent less work per capita, totaling differences in employment and hours, is performed than among non-Hispanic white men.<sup>1</sup> These differences are larger than any differences in total measured work effort implied by differing non-work time at work. But while these racial/ethnic differences in employment and hours are very well documented, the differences on which we focus are non-zero and have not been examined to date.

## **II. ATUS Measures of Time Use on the Job**

As part of its daily diaries, the ATUS includes information on where the respondent was located during each of most of the activities that were undertaken, with one possibility being “at the workplace.”<sup>2</sup> Work and work-related activities constitute the primary activity for most time at the workplace, and we assume that it represents productive time; but respondents also indicate being at the workplace during other primary activities, such as eating at work, “socializing, relaxing and leisure,” “sports and exercise” and “security procedures”. These categories also include employer-sanctioned breaks or self-initiated “down time” in work schedules. We combine all time spent in primary activities at work that the diarist categorizes as other than work or work-related and divide by reported (in the diary) total time at the workplace to create  $\eta$ , 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. One might regard some of these non-

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<sup>1</sup>Own calculations based on the CPS-MORG files for 2014-16.

<sup>2</sup>For most activities in the ATUS, the respondent is asked "Where were you while you were [ACTIVITY]". Respondents can report any location while working, including home, restaurant or the respondent's workplace. (This 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.

work activities as productive, as are many off-the-job activities (e.g., exercise, sleep and many others); but 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.

One may be concerned that recollection of non-work at work on the next day might be hazier than some other activities of equal duration. Perhaps so, but non-work seems at least as easily recollected as time spent in job search in the ATUS, which has already been extensively analyzed in the economics literature (e.g., Aguiar *et al.*, 2013). Even if for some reason 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.<sup>3</sup>

The first decade of ATUS diaries, 2003-12, included over 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 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 Hispanic; Asian-American, and Other races.<sup>4</sup>

In Table 1 we present estimates of  $\eta$ , 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; but there are substantial differences in the  $\eta$  within each gender across

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<sup>3</sup>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, which estimates from the roughly quinquennial May CPS from 1973-91 suggest vary by race. In any case, because all but the raw fractions of time spent not working at the workplace have adjusted for both reported usual weekly hours and recorded diary work hours, reporting problems of this sort are obviated.

<sup>4</sup>We classify as Non-black Hispanic any respondent whose race is not African-American and who lists ethnicity as Hispanic.

the racial ethnic 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 differences across the groups that we explore in the next section.

There is no perfect external verification of these numbers, no exact comparison; the ATUS is the only time-diary survey anywhere to offer this detailed a breakdown of time spent at the workplace. An internet survey conducted in 2012, however, provides a bit of corroborating evidence (Salary.com, 2018). While we create our measure of non-work from daily time-dairies, 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 with our data. But 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 not working at the workplace.

Differences in educational attainment are an obvious first explanation of differences between minority and majority workers. If we divide the sample between those with at least a college education and others, 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-educated and less-educated workers. Only among less educated Asian-American males 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  $\eta$  is nearly identical between Non-Hispanic white men and women. For workers of each gender about 6.5 percent of time at the workplace is spent not working—about a half hour in a full work day.<sup>5</sup> 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

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<sup>5</sup>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.

racers spend greater fractions of their time in non-work activities at their worksites than their female counterparts, while Asian-American male workers spend less.

One might be concerned that the samples are unrepresentative in various ways, perhaps due to 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 American Community Survey (ACS) averaged over 2003-2012 (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 absolutely among the three largest racial/ethnic groups.

### **III. Accounting for Other Demographic, Industry and Occupational Influences**

#### *A. Adjusting for Vectors of Observables*

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, because they could stem from differences in the amount of time spent at the workplace or in the number of hours usually worked; from differences in labor supply due to family circumstances; perhaps from differences in location, or in the state of the aggregate labor market, the day of the week or month of the year for which the time diary is completed; or from differences arising from differential occupation/industry attachment; In what follows, we estimate OLS regressions describing  $\eta$  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  $\eta$  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  $\alpha_1$  in a version of Equation (1) that excludes the vector of covariates  $Z$ . The equation is:

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

where  $i$  is an individual,  $s$  a state,  $t$  a month/year,  $X$  is the vector of indicators of race/ethnicity, the  $\alpha_j$  are parameters to be estimated, and  $\varepsilon$  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 that may not be viewed as disadvantaged, spend greater fractions of their time at their workplace not working compared to Non-Hispanic whites. They 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 the table we add pairs of quadratics 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 others, the differentials in the first rows of Table 2 may merely be reflecting 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 metropolitan status; a quadratic in potential experience; vectors of five indicators of the ages of the children in the household, and four indicators of the respondent's educational attainment. We also add a vector of indicators of state of residence, given geographic differences in the racial/ethnic distributions of the U.S. 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., 2019), 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 4 of the 8 re-specifications showing a more positive 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 between minority and majority workers.

The estimates thus far do not account for 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. 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  $\eta$ ; but those differentials that had been significantly positive 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.<sup>6</sup>

While this vast array of additional controls leaves the estimated differentials for the two largest group positive and statistically significant, their declines are interesting, as are the sources of these drops—among the occupation indicators, the industry indicators, and union status. To examine what causes the reduction in the estimates, we implement Gelbach’s (2016) order-invariant decomposition of the changes in the adjusted estimates of  $\eta$ . Among African-American men, the majority of the decline in the estimated  $\eta$  is accounted for by the addition of the vector of occupational indicators; among Non-black Hispanic men, almost half is explained by the addition of the vector of industry indicators; among women, the declines cannot be accounted for by either of these, nor by union status, but instead are entirely residual.

While the descriptive statistics in Table 1 allowed comparisons by racial/ethnic group of gender differences in worksite non-work, they did not account for differences that might arise from any gender differences in the large sets of controls that we added to generate the estimates in most of Table 2. To obtain

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<sup>6</sup>If we re-estimate these final equations dropping time spent eating at the workplace, the racial-ethnic differentials for male workers are proportionately even larger, while 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 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 percent of workers who report spending at least 50 percent of their time on the job in non-work. Excluding these respondents from the estimates does not qualitatively change the results.

an adjusted gender difference in on-the-job non-work we re-estimate the equation in the last rows of Table 2 over all 35,548 workers in the sample. All these other things equal, male workers spend an additional fraction of 0.001 (s.e.= 0.002) of the time at the worksite not working compared to female workers. The conclusion of little gender difference conveyed by the raw differences in Table 1 is supported even after accounting for large numbers of possible covariates. While there are significant racial/ethnic differentials in non-work at the workplace, there is essentially no difference between otherwise identical male and female employees.

### *B. Robustness—Supply Side Effects*

Since the estimated effects result from interactions between workers and employers, it is generally impossible to identify supply and demand effects separately. Nonetheless, certain characteristics of workers and their workplaces can be more readily linked to supply behavior (demographic differences) or demand behavior (differences in the organization of work). We first consider the differences 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 distinguished by their educational attainment.

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 sub-samples of Asian-Americans and members of Other races render probability statements about their differences from majority workers useless. (Nonetheless, indicators for these other groups are included in the estimates, simply not reported here.) The first two columns present the results for college graduates; the second two columns present 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 tiny 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 differences in behavior generated by differences in educational attainment.<sup>7</sup>

The estimates in Table 2 did not account for the possibility that limitations on health might limit the fraction of work time spent working, and that these might differ by race/ethnicity, because information on respondents' health was not collected in some years in our sample period. For those five years in which such data are available, 2006-08 and 2010-11, we divide the samples into the slightly more than half of the sample who reported being in excellent or very good health, and the slightly smaller group of those respondents who say they are in less than very good health.<sup>8</sup> The estimates of the final equations in Table 2 over 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, the racial/ethnic difference in non-work time at the workplace arises mainly among workers who are not at least in very good health. The opposite result is seen for Non-black Hispanic women. In these data 64 percent of white non-Hispanic employees report being in at least very good health, while only 50 percent of African-American employees do. 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 tiny as to prevent disaggregating the samples of women by veteran status. Among men, however, in these samples 17 percent of African-American workers are military veterans, while 14 percent of Non-Hispanic whites are, as are 4 percent of Non-black Hispanic workers. Perhaps having served in the military alters behavior in the workplace; or perhaps self-selection into the military is related to some characteristic that also causes

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<sup>7</sup>The influence of age on non-work time may differ between majority and minority workers. To examine this, we created an indicator,  $\text{age} \leq 40$ , 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.

<sup>8</sup>This is a subjective (self-)assessment of the person's health. Nonetheless, other evidence (Bound, 1991) suggests 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 evidence (Dowd and Todd, 2011) demonstrates racial/ethnic differences in responses to subjective questions about health status.

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, presenting the results in the bottom row of each 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. The entire differences between Non-Hispanic whites', African-American and Non-black Hispanic workers' reported time spent not working at the workplace stem from differences generated by the overwhelming majority of minority workers who are not military veterans.

### *C. 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 sub-samples of workers, the first of public employees, the second of private.

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 is driving the results in Table 2, and since the racial/ethnic differences there were larger among men, our results suggest that this source of possible differences in structure of monitoring is not producing 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, 2018, 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 rows 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, so that the results overall do not support the importance of differential monitoring by method of payment.<sup>9</sup>

Although the decompositions in Sub-section A showed 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), perhaps arising from 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 over these sub-samples too. 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.

#### **IV. Possible Explanations**

Aggregating the adjusted effects among men, based on the results in Section III, 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 percent 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 their workplaces. Taking all four female minority groups together, the weighted average of the estimates suggests that the average minority female worker spends 0.64 percent less of each workday actually working at the worksite compared to her majority counterparts, i.e., 14 hours of a full-time work year.<sup>10</sup> The evidence in Sub-sections III.B. and III.C indicates

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<sup>9</sup>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 the middle rows of Table 4.

<sup>10</sup>One might argue that the differences that 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

that, except most importantly 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 arise from a greater willingness of minorities to report non-work time on the job or from racial/ethnic differences in views about what constitutes actual work? 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 had less time to assimilate to the behavior of the majority.

To examine 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 do not show the results here, leaving them for Appendix Table A.1. Among immigrants, however, African-Americans do differ more from Non-Hispanic whites than is true 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, for the two largest minority groups the additional non-work time among natives 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) different activities per day on average, while the average numbers of different activities 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), Other races, 19.63 (s.e.=0.188). Minorities report fewer different activities per day than otherwise identical majority workers, not more.

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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, 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 (women) by about 10 (15) percent.

Some additional evidence that these results do not merely arise from differing willingness to report non-work due to racial differences in the social desirability of work comes from analyses of the General Social Surveys. The GSS has included two questions that allow examining 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, agreement with the statement, “My main satisfaction in life comes from work.” Estimating a probit (ordered probit) on the responses to Question 1 (2) and excluding racial groups other than whites and African-Americans due to lack of information, the latter are insignificantly more likely to say they would stop work; but they are also nearly significantly more likely to agree or agree strongly with the statement about the importance of satisfaction with work. (See Appendix Table A2 for results.) There is clearly no racial difference in how people view the desirability of work, suggesting (but hardly proving) that differences in willingness to report non-work at work are unimportant.

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 “down time.” Clearly, with these data we cannot investigate this explanation. Still another alternative is that the extra non-work time at the workplace reported by minority employees enables them to be more productive than majority employees during the (lesser) amount of time per hour on the job that they are actually working (consistent with some older, very loosely related indirect evidence—Hellerstein *et al.*, 1999).

Minorities may spend more workplace time not working since discriminatory practices lower the returns to effort – especially regarding promotion and long-term career prospects – and thus the long-term penalties for non-work. A weak test of the validity of this explanation is provided by comparing self-employed minority to their majority counterparts. Since self-employed workers cannot be promoted, if employer discrimination in promotion probabilities explains our results, we would not see racial/ethnic differences among the self-employed. Work time at the worksite by minority self-employed might,

however, be below that of majority self-employed workers if customer discrimination reduces the gains to marginal increases in work time.

To examine this possibility, Table 5 shows the mean non-work time of majority and minority employees and self-employed workers by gender. Among minority self-employed workers the mean is lower than that among minority employees shown in Table 1; but the same is true between 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 among self-employed male and female workers yields the same conclusion: The additional non-work time 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 that there is no difference in the relative amounts of non-work at the workplace. This weak test rejects that possibility that responses to discriminatory promotion practices are generating our results. These may exist, but in this context their impact is equal to that of any impacts of 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 non-work compensates for their extra stress. We can examine this possibility using two data sets. First, in 2003 the 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 equal, African-American men are less likely to say 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 several years 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 no stress to 6 indicating the respondent felt very stressed during that activity. We estimate activity-level ordered probits over this measure. The estimates suggest that, other things equal, African-Americans are significantly **less** likely to state that they were stressed during randomly selected activities. The differences for Non-black Hispanics and Asian-Americans are small and negative, with t-statistics below one, while that for Other races is 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.<sup>11</sup>

Our results cannot be explained by a whole 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. They might also arise from more basic differences (which in turn could well result from a long history of discrimination). In the end the best conclusions are that racial/ethnic differences in non-work time at the workplace are real, that we have ruled out a variety of explanations for them, but that discerning their ultimate cause(s) requires substantial additional work that is beyond the scope of any of the data used here.

#### **V. The Economic Significance of Racial-Ethnic Differences in Non-Work at the Workplace**

While statistically significant and robustly so, these estimates of racial/ethnic differences are not large. To what extent 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 *et al.*, 2018) estimated adjusted black-white wage differentials at around 14 percent, Hispanic- Non-Hispanic white adjusted wage differentials at around 15 percent, Asian-American wage differences at around 13 percent, and white-Other races differences at around 14 percent. D’Haultfoeuille *et al.* (2018) found median estimates of the African-American-white wage gap using samples from the NLSY79 and NLSY97 of around 12 percent.

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<sup>11</sup>These ATUS results and the PSID estimates discussed in the preceding paragraph are presented in Appendix Table A3.

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 2003-12 were in the CPS in those years), and to use larger samples, we specify log-earnings equations using the CPS-MORG for 2014-16. Estimates of the racial/ethnic effects on log-earnings are presented for men and women 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) The earnings differentials are smaller for women than for men; and 2) Adding the vectors of occupation/industry indicators reduces the measured differentials for these groups by one-third to one-half. These earnings differentials measure:

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

where E is weekly earnings, H usual weekly hours as reported, m indicates minority and w indicates majority.<sup>12</sup>

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

$$(3) \quad D' = D - [x_w - x_m],$$

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<sup>12</sup> Some of the wage differentials may reflect the possibility that earnings as measured already account for differences in non-work at work. While we cannot identify this compensating differential, we can 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 or not the worker reports any on-the-job non-work. Those who report some non-work, averaging 10 percent of the workday, receive 2 percent lower wages, other things equal. Thus only part of non-work time results in a wage penalty, suggesting but, because of the identification problem, not proving, that it is correct to adjust observed racial/ethnic earnings differentials for differences on non-work time.

noting that  $\ln(1-x)$  is approximately  $-x$ , where the estimated  $x_m$  in (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,  $D$ , 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 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 percent reduction), and among African-American women by over one-half percentage point.

These effects are modest in magnitude and smaller than well-known racial/ethnic differences in earnings/capita that are attributed to racial/ethnic differences in employment rates and hours per worker. But in comparison, they 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 *et al.*, 2016). They suggest some revisions in thinking about the racial/ethnic wage differentials that have received so much attention from social scientists.

## **VI. 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 percent in the estimated earnings/effort disadvantage of African-American and Non-black Hispanic men.

We rejected a large range of explanations for the differences in effort based on incentives at work facing minorities. Similarly, they are not explained by differences 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 engaged in while 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 differences 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, putting the scientific management studies of the post-World War I era (e.g., Florence, 1924) on a much more general and more broadly applicable basis.

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**Table 1. Non-work Time at Work and Ethnic Representation, ATUS Employees, 2003-12\***

	<b>Non-Hispanic White</b>	<b>African- American</b>	<b>Non-black Hispanic</b>	<b>Asian- American</b>	<b>Other races</b>
<b>MEN</b>					
Fraction of Workplace Time Not Working	0.0645 (0.0022)	0.0793 (0.0063)	0.0848 (0.0055)	0.0679 (0.0099)	0.0701 (0.0133)
N =	12,348	1830	2582	651	366
Share of Race/Ethnicity in:**					
ATUS Sample	0.695	0.102	0.145	0.037	0.021
ACS	0.693	0.097	0.145	0.044	0.021
<b>WOMEN</b>					
Fraction of Workplace Time Not Working	0.0646 (0.0023)	0.0758 (0.050)	0.0779 (0.0058)	0.0724 (0.105)	0.0649 (0.129)
N =	11,877	2787	2137	605	365
Share of Race/Ethnicity in:**					
ATUS Sample	0.668	0.156	0.120	0.034	0.022
ACS	0.687	0.127	0.118	0.045	0.023

\*Standard errors in parentheses. These means and the estimates reported in Tables 2-7 are all based on ATUS final sampling weights.

\*\*Rounded to add to 1.

**Table 2. Parameter Estimates, Racial/Ethnic Effects on the Fraction of Worktime Not Working, ATUS Employees, 2003-12 (Base Group Is Non-Hispanic Whites)\***

Equation	African- American	Non-black Hispanic	Asian- American	Other races	R- bar <sup>2</sup>
	MEN (N=17,777)				
Raw differential	0.0148 (0.0036)	0.0203 (0.0031)	0.0034 (0.0036)	0.0056 (0.0059)	0.005
Add hours, demographic and geographic indicators**	0.0120 (0.0036)	0.0198 (0.0034)	0.0091 (0.0039)	0.0078 (0.0062)	0.079
Add very detailed industry, occupation and union indicator***	0.0076 (0.0031)	0.0151 (0.0029)	0.0082 (0.0047)	0.0027 (0.0060)	0.112
	WOMEN (N=17,771)				
Raw differential	0.0112 (0.0027)	0.0132 (0.0034)	0.0078 (0.0057)	0.0025 (0.0063)	0.002
Add hours, demographic and geographic indicators**	0.0113 (0.0030)	0.0093 (0.0039)	0.0091 (0.0062)	-0.0037 (0.0066)	0.085
Add very detailed industry, occupation and union indicator***	0.0085 (0.0028)	0.0067 (0.0032)	0.0058 (0.0048)	-0.0044 (0.0062)	0.112

\*Standard errors of parameter estimates in parentheses.

\*\*Quadratics in daily work time, usual weekly hours, and potential experience; vectors of indicators of education, of age of youngest child, of states, years, months, and days of the week; indicators of marital and metro status.

\*\*\*Indicators for 513 occupations, 259 industries, and union membership.

**Table 3. Supply-side Robustness Checks, Excess of Non-work Time over Non-Hispanic Whites Among African-Americans and Non-black Hispanics, ATUS Employees, 2003-12\***

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

\*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.

\*\*Includes only observations for 2006-08, 2010-11, since information on health was only collected in those years.

**Table 4. Demand-side Robustness Checks, Excess of Non-work Time over Non-Hispanic Whites Among African-Americans and Non-black Hispanics, ATUS Employees, 2003-12\***

<b>MEN</b>							
<b>African-American</b>	<b>Non-black Hispanic</b>	<b>N</b>	<b>R<sup>2</sup></b>	<b>African-American</b>	<b>Non-black Hispanic</b>	<b>N</b>	<b>R<sup>2</sup></b>
<b>Public employees</b>				<b>Private employees</b>			
0.0024 (0.0085)	0.0124 (0.120)	2,687	0.234	0.0075 (0.0042)	0.0154 (0.0035)	15,090	0.109
<b>Hourly</b>				<b>Salaried</b>			
0.0080 (0.0049)	0.0137 (0.0049)	9,609	0.128	0.0023 (0.0058)	0.0147 (0.0056)	8,168	0.123
<b>Union member or covered</b>				<b>Non-union</b>			
0.0025 (0.0095)	0.0110 (0.0123)	2,721	0.190	0.0099 (0.0042)	0.0155 (0.0035)	15,056	0.111
<b>WOMEN</b>							
<b>African-American</b>	<b>Non-black Hispanic</b>	<b>N</b>	<b>R<sup>2</sup></b>	<b>African-American</b>	<b>Non-black Hispanic</b>	<b>N</b>	<b>R<sup>2</sup></b>
<b>Public employees</b>				<b>Private employees</b>			
0.0165 (0.0059)	0.0333 (0.0117)	3,553	0.101	0.0066 (0.0037)	0.0025 (0.0043)	14,218	0.122
<b>Hourly</b>				<b>Salaried</b>			
0.0057 (0.0042)	0.0023 (0.0055)	10,941	0.135	0.0123 (0.0046)	0.0084 (0.0056)	6,830	0.118
<b>Union member or covered</b>				<b>Non-union</b>			
0.0179 (0.0086)	0.0139 (0.0171)	2,245	0.275	0.0069 (0.0344)	0.0060 (0.0040)	15,526	0.113

\*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.

**Table 5. Mean Fraction Non-work at Work, and Parameter Estimates and Minority Effects on this Fraction, ATUS Self-Employed Workers, 2003-12\***

	<b>Non- white</b>	<b>Hispanic American</b>	<b>Non-black Hispanic</b>	<b>Asian- American</b>	<b>Other races</b>	<b>R-bar<sup>2</sup></b>
<b>MEN (N=2,342)</b>						
Average fraction non-work	0.0472 (0.0030)	0.0532 (0.0111)	0.0587 (0.0073)	0.0481 (0.0066)	0.0328 (0.0087)	
Full set of controls**		0.0166 (0.0265)	0.0082 (0.0115)	0.0284 (0.0127)	0.0057 (0.0183)	0.154
<b>WOMEN (N=1,005)</b>						
Average fraction non-work	0.0531 (0.0048)	0.0724 (0.0191)	0.0427 (0.0101)	0.0284 (0.0080)	0.1349 (0.0743)	
Full set of controls**		0.0107 (0.0199)	0.0001 (0.0157)	-0.0270 (0.0239)	0.1327 (0.1117)	0.211

\*Standard errors of means in parentheses below the raw averages, and standard errors of estimates below them.

\*\*The equations include all the controls in the final equation presented in Table 2

**Table 6. Parameter Estimates, Racial/Ethnic Effects on ln(Weekly Earnings), CPS Employees, 2014-16, and Adjustments for Differential Non-Work at the Workplace (Base Group is Non-Hispanic Whites)\***

	African-American	Non-black Hispanic	Asian-American	Other races	R-bar <sup>2</sup>
	<b>MEN (N=187,242)</b>				
**Adjusted earnings differential (from CPS regression)	-0.171 (0.004)	-0.157 (0.003)	-0.083 (0.007)	-0.054 (0.010)	0.614
Accounting for non-work	-0.159	-0.137	-0.074	-0.046	
***Adjusted earnings differential (from CPS regression)	-0.104 (0.004)	-0.093 (0.004)	-0.053 (0.007)	-0.033 (0.009)	0.670
Accounting for non-work	-0.096	-0.078	-0.045	-0.030	
	<b>WOMEN (N=173,739)</b>				
**Adjusted earnings differential (from CPS regression)	-0.109 (0.004)	-0.122 (0.004)	-0.056 (0.007)	-0.042 (0.010)	0.656
Accounting for non-work	-0.098	-0.113	-0.047	-0.046	
***Adjusted earnings differential (more detailed controls) (from CPS regression)	-0.057 (0.004)	-0.061 (0.004)	-0.028 (0.006)	-0.024 (0.009)	0.711
Accounting for non-work	-0.048	-0.054	-0.022	-0.028	

\*Standard errors of parameter estimates in parentheses.

\*\*Quadratics in usual weekly hours, and potential experience; vectors of education indicators, of age of youngest child, of states, of years and months, and indicators of marital and metro status.

\*\*\*Adds indicators for 513 occupations, 259 industries, and union membership.

**Appendix Table A1. Parameter Estimates, Native and Immigrant Sub-samples (Racial-Ethnic Effects with Non-Hispanic Whites as the Base Group)\***

	<b>African-American</b>	<b>Non-black Hispanic</b>	<b>Asian-American</b>	<b>Other races</b>	<b>N</b>	<b>R-bar<sup>2</sup></b>
<b>MEN</b>						
<b>Natives</b>	0.0042 (0.0041)	0.0181 (0.0057)	0.0032 (0.0115)	0.0069 (0.0075)	14,633	0.122
<b>Immigrants</b>	0.0253 (0.0111)	0.0105 (0.0070)	0.0004 (0.0070)	-0.0133 (0.0112)	3,144	0.139
<b>WOMEN</b>						
<b>Natives</b>	0.00083 (0.0034)	0.0073 (0.0058)	-0.0055 (0.0089)	-0.0037 (0.0082)	15,273	0.121
<b>Immigrants</b>	0.0132 (0.0095)	0.0102 (0.0953)	0.0174 (0.0110)	-0.0117 (0.0123)	2,498	0.192

\*Standard errors in parentheses below the parameter estimates here and in Appendix Tables A2 and A3. The equations include all the controls used in the final equation presented in Table 2.



**Appendix Table A3. Parameter Estimates, Racial/Ethnic Effects on Stress (with non-Hispanic Whites as the Base Group)\***

	<b>African-American</b>			
<b>Data Set and Dep. Var.:</b>	<b>MEN</b>	<b>WOMEN</b>		
PSID 2003, Married*	-0.0597	-0.1039		
Probit on indicator	(0.0354)	(0.0271)		
always/often stressed				
N =	1,649	2,189		
	<b>African- American</b>	<b>Non-black Hispanic</b>	<b>Asian- American</b>	<b>Other races</b>
	<b>ALL</b>			
ATUS 2010, 2012**				
Ordered probit, stressed during	-0.2447	-0.0037	-0.0132	0.1574
activity, 6 to 0 scale	(0.0513)	(0.0436)	(0.1288)	(0.0847)
N = 40,817				

\*Includes each spouse's earnings, hours of work and health status, and family income and the ages and numbers of children.

\*\*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.