Racial Differences in Time at Work Not Working

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RACIAL DIFFERENCES IN TIME
AT WORK NOT WORKING

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Racial differences in effort at work, if they exist, can potentially explain race-based wage/earnings disparities in the labor market. The authors estimate specifications of time spent on non-work activities at work by Black and White males and females with data from the American Time Use Survey. Estimates reveal that trivially small differences occur between non-Hispanic Black and non-Hispanic White males in time spent not working while on the job that disappear entirely when correcting for non-response errors. The findings imply that Black–White male differences in the fraction of the workday spent not working are either not large enough to partially explain the Black–White wage gap, or simply do not exist at all.

Apersistent drumbeat in social science research ascribes Black–White differences in outcomes and actions to differences in behavior caused by cultural factors, particularly those that are unobservable (Neumark and Rich 2019). Black behavioral practices typically are characterized as dysfunctional, contributing directly to negative economic results (Mason 2004). From this perspective, Blacks do not receive lower wages primarily because of discrimination but, instead, because their cultural orientation predisposes them to be less productive in the workplace.

A recent version of this line of thinking appears in a study by Hamermesh, Genadek, and Burda (2017, 2019)—hereafter H-G-B—that suggested Blacks may be more predisposed to shirking. Utilizing data from the American Time Use Survey (ATUS), H-G-B found that non-White men

spend a greater fraction of their workday not working relative to White non-Hispanic men, and failing to account for this difference overstates the associated wage/earnings differentials in the labor market. They concluded:

> 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. (Hamermesh et al. 2019: 289)

We ask and answer the following methodological question in this article: Are the H-G-B findings robust across alternative model specifications, estimation techniques, and corrections for the widely known racial differences in response rates in the ATUS? The importance of asking and answering this question lies in how policymakers and their research advisors interpret statistical findings of racial disparities in labor markets.

The article uses the ATUS data for 2003 to 2015; replicates the H-G-B findings; and tests the hypothesis that these findings prevail after accounting for non-response bias, truncation bias, and biases associated with censoring and upper and lower bounds of time use. We provide linear, log-linear, censored Tobit, and unconditional quantile parameter estimates with and without ATUS weights, non-response weights, censoring on non-work time, time fixed effects, and metro area fixed effects to determine whether non-Hispanic Black males spend less time at work not working than do non-Hispanic White males.[1]

Our inquiry contributes to the broad literature on the indirect analysis of labor market consequences of race, as we utilize a regression-based approach to determine whether racial identity conditions work effort on the job. As our econometric specifications of the time spent not working on the job acknowledge the possibility of group-based differences in preferences for work effort on the job, our findings inform the extent to which differential non-Hispanic Black and non-Hispanic White male wage/earnings disparities can be explained by work-effort disparities. We argue that a persistent historical perception exists regarding Blacks' work effort—defined as the "Stepin Fetchit Hypothesis"—that informs and influences policy analysis on racial disparities in labor markets.

Our inquiry also makes a contribution to stratification economics (Darity 2005; Darity, Hamilton, and Stewart 2015), with respect to scrutinizing a

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[1]We examine racial differences between non-Hispanic Black men and non-Hispanic White men. For the rest of the article, the Black men and White men respondents are exclusive of Hispanic.

particular and possible alternative rationalization of Black–White male wage/earnings disparities (Mason 1999; Coleman 2003). In particular, to the extent that relative Black laziness is a historical stigma that rationalizes race-based inequality (Davis 2014), our results will inform the scope for the rationalization of existing Black–White wage/earnings disparities on the basis of Black–White work intensity disparities.

Stereotypes and Explanations for Racial Disparities in Work Effort

One of the enduring legacies of Jim Crow racial subordination of Black Americans in the United States is the stereotype and perception among Whites that Blacks are lazier than Whites (Reyna 2000; DeSante 2013). We refer to this stereotype as the Stepin Fetchit hypothesis, the supposition that Blacks, unlike Whites and perhaps other non-Blacks, find as many ways as possible to put forth low work effort. Stepin Fetchit was a character played in the movies by actor Lincoln Perry, noted for his shuffling, slow-speaking manner, often dim-witted with a notorious inclination to do as little work as possible (Hurst 2006). Ironically, Stepin Fetchit displays his greatest degree of ingenuity in finding multiple ways to avoid doing work. The character became hugely popular with American White cinema audiences during the 1930s, leading Perry to become the first Black actor to earn $1 million in a single year. In what follows, we offer a new assessment of the Stepin Fetchit hypothesis as we empirically explore the extent to which, relative to Whites and non-Blacks, Blacks withhold work effort, which would be consistent with the stereotype of the relatively lazy Black employee.

Since laziness can be gauged by effort intensity in employment, actual relative Black–White laziness in work effort can potentially drive Black–White wage disparities, thereby reducing the unexplained Black–White wage/earnings gap typically assigned to labor market discrimination (Hamermesh et al. 2017, 2019).[2] To the extent that low effort intensity increases worker monitoring costs, which, in turn, can reduce firm profitability, the perception of Black workers being lazy may even cause employers to avoid hiring them altogether, generating Black–White unemployment disparities in the labor market (Pager and Shepard 2008; Bartos, Bauer, Chytilova, and Matejka 2016). Examination of sensible proxies for effort intensity at work is potentially valuable in assessing the extent to which such disparities occur in work effort and performance (McKay and McDaniel 2006) that can possibly translate into Black–White disparities in wages and earnings. If preferences for work hours between non-Whites and Whites are identical, and one can distinguish between employee and employer preferences for

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[2]The 2019 article published in the *ILR Review* is based on the 2017 NBER Working Paper (No. 23096) with the same title, "Racial/Ethnic Differences in Non-Work at Work." The assumptions and conclusions of the NBER and the *ILR Review* versions of the paper remain essentially the same. One notable omission in the published version is the disturbing cultural explanation for the observed racial differences in time use.

work hours (Pencavel 2016), H-G-B's results are compelling. Certainly, one should account for the possible bias that could result from Whites and Blacks having different preferences for work hours (Bell 1998). Furthermore, differential response rates across non-Hispanic Black and non-Hispanic White respondents could result in samples that are not representative of race-specific work effort preferences in the relevant population, leading to biased parameter estimates (Kim and Kim 2007).

But, what if the stereotypes—accurate or not—influence hiring decisions or influence employee work effort? What if these enduring stereotypes persist even when Black workers are highly productive? What if the legacy of these sterotypes is to cause researchers and policymakers to interpret unobserved components of racial gaps in labor markets to culture or behaviors by Blacks themselves and to dismiss allegations of employer discrimination? The analysis that follows helps to address these questions.

Data and Methodology

The source of our data is the publicly available IPUMS-ATUS (Integrated Public Use Microdata Series–American Time Use Survey) for the years 2003 to 2015 (Hofferth, Flood, Sobek, and Backman 2020). Collected annually since 2003, the ATUS samples individuals who are randomly selected from a subset of households that have completed their eighth month interviews for the Current Population Survey (CPS). The ATUS captures individual-level measures of time spent on activities such as work, leisure, and household chores and provides data on the specific location of time use, enabling a determination of how time is used at work.

Table 1 shows the non-response rates for 2003 to 2015. Notably, 42.2 to 51.5% of respondents selected from the outgoing rotation of the CPS did not respond to the ATUS. Figure 1 shows that the non-response rates for non-Hispanic Blacks are higher than the non-response rates for non-Hispanic Whites. The non-response rates spiked in 2007 and declined for both Blacks and Whites in 2008 and 2009, before a steady rise and near convergence in non-response rates across racial groups through 2015.

Table 2 reports the weighted means of characteristics of respondents and non-respondents. The rows are sorted by the percentage differences between White non-respondents and respondents. Three conclusions immediately emerge: 1) respondents and non-respondents differ in nontrivial ways; 2) the factors beyond the obvious ones—such as not having a phone—differ between non-Hispanic Blacks and non-Hispanic Whites; and 3) the rate of difference between respondents and non-respondents is not always consistent across race.

Three noteworthy disparities between non-Hispanic White non-respondents and respondents include US citizenship, low educational attainment, and physical or cognitive disability. Among non-Hispanic Whites, these categories are associated with non-respondents. Among non-Hispanic Blacks,

Table 1. Non-Response Rates in ATUS (2003 to 2015)

Year	Non-response rate (%)
2003	42.2
2004	42.7
2005	43.4
2006	44.9
2007	47.5
2008	45.4
2009	43.4
2010	43.1
2011	45.4
2012	46.8
2013	50.1
2014	49.0
2015	51.5

Source: American Time Use Survey User's Guide:
Understanding ATUS 2003 to 2015.

the differences between respondents and non-respondents are much smaller for the same three factors.

Both non-Hispanic Black and non-Hispanic White respondents and non-respondents differ in age, higher education, marital status, and whether they have more than one job. Respondents are older, more likely to have a college degree, more likely to ever have been married, and more likely to have more than one job during the reference period.

We estimate the probability of not answering the ATUS in Equation (1), where *Pit* is the probability of not answering ATUS in year *t*; $\boldsymbol{B}$ is a binary indicator for whether the respondent is a non-Hispanic Black; $\boldsymbol{X}$ is a vector of demographic and regional controls; and ε is a stochastic error. If a significant difference in not answering the ATUS between non-Hispanic Blacks and non-Hispanic Whites is evident, we generate the "non-response weight" as a robustness check beside the ATUS official weights. It equals the inverse probability of not responding to the ATUS survey (Scharfstein, Rotnitzky, and Robins 1999; Wooldridge 2007).

$$(1) \qquad ln\left(\frac{p_{it}}{(1-p)_{it}}\right) = \beta_0 + \beta_1 \boldsymbol{B} + \gamma_i X_{it} + \varepsilon_{it}$$

Following H-G-B, we construct a variable that, for each ATUS respondent, sums all time spent—in minutes—in primary activities at work other than job-related activities, and divide it by total time at the workplace, denoted as η_{it}. This ratio represents the fraction of time that the person is not working while at the workplace. We exclude self-employed people and people who are working remotely from their homes in order to better capture a measure of time spent at workplaces, since the boundaries of work and

Figure 1. Non-Response Rates by Race in ATUS (2003 to 2015)
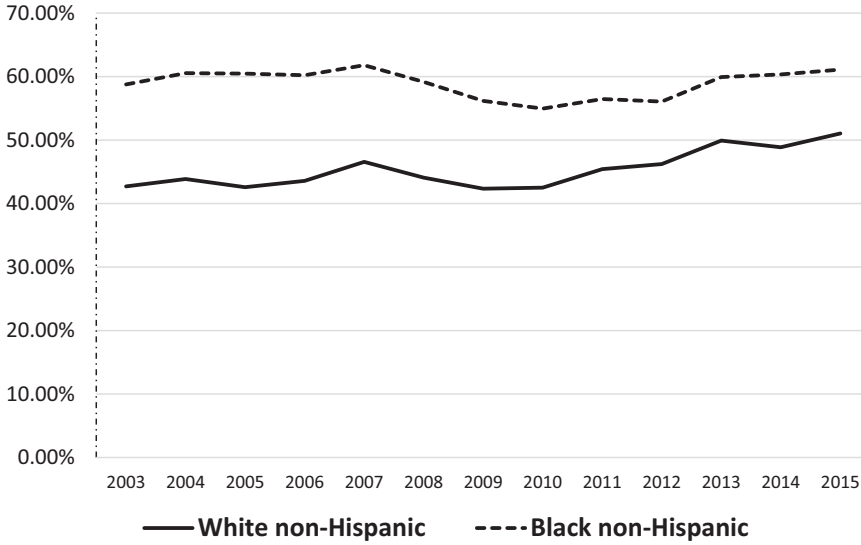
Notes: ATUS, American Time Use Survey.

non-work for self-employed and remotely working people are sometimes not clear.

Defining the fraction of time the person is not working while at the job site as η, we posit that for ATUS respondent i at time t in Equation (2), where $\boldsymbol{B_m}$ is a binary indicator for whether the respondent is a non-Hispanic Black male; $\boldsymbol{X}$ is a vector of demographic, industry, occupation, time, and geographic controls; and ε is a stochastic error.

$$(2) \qquad\qquad \eta_{it} = \beta_o + \beta_1 \mathbf{B_m} + \gamma_i \mathbf{X}_{it} + \varepsilon_{it},$$

One non-trivial discovery is that more than 34% of the non-self-employed respondents report zero-minute non-working time with non-zero total time at the workplace (the non-zero numerator of η). Table 3 presents the percentiles of η for both non-self-employed non-Hispanic Whites and non-Hispanic Blacks. In particular, 37.22% of non-self-employed, non-Hispanic Whites reported zero minutes on non-work activities at the workplace and 29.56% of non-self-employed non-Hispanic Blacks reported zero minutes on non-work activities at the workplace.

As robustness checks, we first exclude the zero-minute reporters to allow for the possibility that respondents are possibly reporting falsely and/or in error spending zero time at their job site not working. Next, we impose a non-zero lower bound on workplace non-work activities. We assume every respondent spent at least one minute at the workplace in non-work activities, a reasonable non-zero lower bound for the numerator for η. Panel B of Table 3 displays the percentile distribution of η with the one-minute lower

Table 2. Means of Characteristics of Respondents and Non-respondents, by Race in ATUS (2003 to 2015)

	White Non-Hispanic			Black Non-Hispanic		
	Respondents	*Non-respondents*	*Percentage difference*	*Respondents*	*Non-respondents*	*Percentage difference*
No phone available	0.0179	0.0417	**133.28**	0.0589	0.0810	**37.60**
Phone available; not in household	0.0044	0.0075	**70.66**	0.0075	0.0119	**58.65**
Non-citizen	0.0138	0.0197	**42.72**	0.0328	0.0387	**17.92**
Naturalized citizen	0.0188	0.0256	**36.14**	0.0375	0.0404	**7.64**
Less than high school	0.0991	0.1283	**29.46**	0.1799	0.1919	**6.69**
GED	0.0189	0.0242	**27.70**	0.0213	0.0241	**13.01**
Unemployed in the last year	0.0121	0.0141	**16.98**	0.0210	0.0246	**17.40**
High school	0.2121	0.2409	**13.62**	0.2363	0.2663	**12.70**
South	0.3255	0.3508	**7.79**	0.5750	0.5533	**-3.76**
Hourly paid worker	0.2293	0.2440	**6.39**	0.2678	0.2756	**2.90**
Has any physical or cognitive difficulty (available after year 2008)	0.1373	0.1457	**6.14**	0.1768	0.1578	**-10.70**
Some college	0.1516	0.1552	**2.38**	0.1688	0.1670	**-1.04**
Residence: Metropolitan	0.7894	0.7988	**1.19**	0.8718	0.8879	**1.85**
Female	0.5310	0.5205	**-1.98**	0.5749	0.5571	**-3.09**
West	0.1915	0.1868	**-2.44**	0.0807	0.0855	**5.95**
Recession years (year = 2007, 08, and 09)	0.2224	0.2157	**-3.02**	0.2240	0.2252	**0.53**
Age	43.0993	39.9580	**-7.29**	43.6800	39.4259	**-9.74**
Associate degree	0.0785	0.0726	**-7.49**	0.0757	0.0628	**-17.02**
Ever married	0.6508	0.6013	**-7.61**	0.5420	0.4737	**-12.60**
Midwest	0.2914	0.2607	**-10.54**	0.1948	0.1941	**-0.38**
Bachelor	0.1737	0.1415	**-18.51**	0.1137	0.0918	**-19.29**
Having more than one job	0.0314	0.0224	**-28.47**	0.0249	0.0163	**-34.69**

Notes: ATUS, American Time Use Survey.

Table 3. Time Share of Non-Work Activity (η) at the Workplace by Race, Not
Including Self-Employed Males, ATUS (2003 to 2015)

Panel A: Unweighted distribution of (η)

	White Non-Hispanic	Black Non-Hispanic
5%	0.0000	0.0000
10%	0.0000	0.0000
25%	0.0000	0.0000
50%	0.0408	0.0536
75%	0.0849	0.0976
95%	0.1714	0.1782
Mean	0.0642	0.0749
Mean value for reported non-working minute ≥ 1	0.1023	0.1063

Panel B: Unweighted distribution of (η'), assuming 1 minute lower bound

	White Non-Hispanic	Black Non-Hispanic
5%	0.0016	0.0017
10%	0.0018	0.0019
25%	0.0025	0.0042
50%	0.0417	0.0536
75%	0.0857	0.0976
95%	0.1739	0.1786
Mean	0.0662	0.0762

Notes: ATUS, American Time Use Survey.

bound (η'), and Figure 2 compares the distribution of η and η'. Except for shifting the whole distribution slightly to the right, the results show no change in the shape of the distribution of η.

Another way to solve the high proportion of zero-minute reporters is to adopt a two-part model that corrects the bias from either the non-response or misreported zero-minute value in η_{it} (Heckman 1979; Frondel and Vance 2012). In the first stage (Equation (3)), we define a dichotomous variable R, where $R=1$ indicates that $\eta_{it} > 0$, otherwise $\eta_{it} \leq 0$, and ε_1 is assumed to have a standard normal distribution. We use a Probit model to generate the estimates from the first stage. The two-part model assumes that $E(\varepsilon_2 \mid y > 0, X_{2t}) \neq 0$, implying $E[\eta_{it}|R = 1, X_{2t}] \geq -\beta X_{2t}'$. Then the second stage has the same specification as Equation (2), which is an ordinary least squares (OLS) estimator for η_{it} (Equation (4)).

$$(3) \qquad \left\{ \frac{R = 1, \eta_{it}* = \tau X_1' + \varepsilon_1}{R = 0, \eta_{it}* \leq 0} \right\}$$

$$(4) \qquad E[\eta_{it}|R = 1, X_{2t}] = E[\eta_{it} > 0, X_{2t}] = \beta X_{2t}' + E(\varepsilon_2|y > 0, X_{2t}) = \beta_0 + \beta_1 W_B + \delta_i X_{it}$$

Because no exclusion restrictions are imposed, the nonlinearity of the process that determines selection enables us to identify the parameters of interest (Puhani 2000). Given the possible collinearity between the inverse Mills ratio and the included regressors, which can be exacerbated in the

Figure 2. Distributions of η and η' by Race, not Including Self-Employed Males,
ATUS (2003 to 2015)
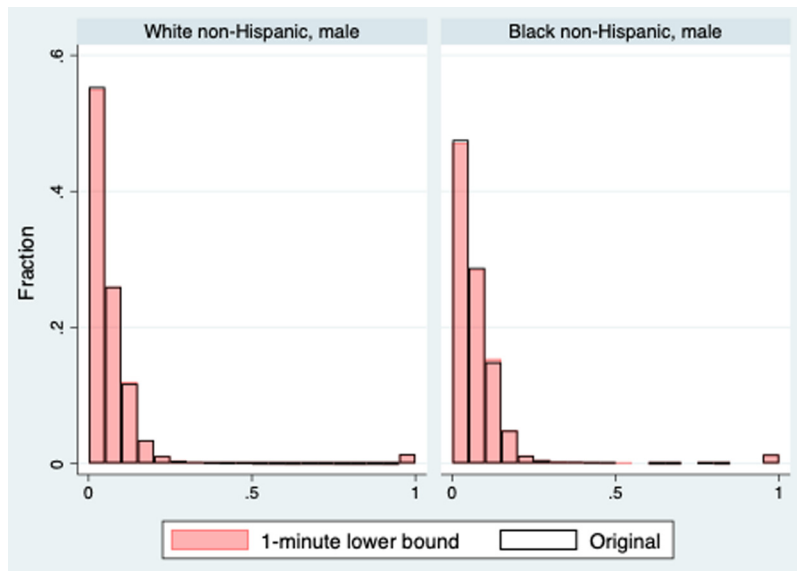
Notes: η = original (i.e., zero-minute lower bound) and η' = 1-minute lower bound. ATUS, American Time Use Survey.

absence of hard-to-find and justified exclusion restrictions (Bushway, Johnson, and Slocum 2007), the estimated parameter standard errors could be imprecise (Stolzenberg and Relles 1990; Moffitt 1999). As such, the parameter estimates in Equation (4) may not strongly identify the effects of interest, as the parameter hypotheses may be based on biased test statistics.

Again, the ATUS unadjusted sample averages in panel A of Table 3 reveal that relative to non-Hispanic White males, non-Hispanic Black males spend approximately 17% more time not working while at work. To the extent this unconditional difference reflects actual racial differences in shirking, estimated Black–White wage and earnings ratios may overstate the extent of labor market discrimination faced by non-Hispanic Black males. Kuhn and Lozano (2008), however, found that the choices of salaried men to work longer hours may reflect endogenous changes in the structure of within-group earnings inequality. If Whites are more likely to be salaried workers and salaried workers are more likely to overestimate their time working, then a differential distribution of Black and White males across hourly versus salaried jobs can render unconditional and conditional biased estimates of η.

To account for the differential distribution of Black and White males in salaried versus hourly jobs that may bias the effects of race on η, we include in X whether an ATUS respondent is employed in an occupation with a high share of hourly jobs, as it may be difficult to shirk in salaried jobs that

require longer hours. To the extent that hourly jobs are also jobs in industries in which leisure and shirking are substitutable, if employees have short commutes—that is, live in proximity to the place of employment—shirking on the job may be easier (Ross and Zenou 2008; Van Ommeren and Gutiérrez-i-Puigarnau 2011). Table 4 reports a summary of the covariates we constructed for estimating various specifications of η_{it}. Relative to non-Hispanic White males, results reveal that non-Hispanic Black males are 27% more likely to be in jobs that are compensated by the hour and are less likely to be subject to working longer hours on the job, the phenomena identified by Kuhn and Lozano (2008).

Well-documented evidence shows union members are protected and are required to take breaks to work efficiently (Clark 1980; Freeman and Medoff 1984). To isolate the net racial effect in η, we control for individual union membership and interaction with highly unionized states. As the literature suggests, high union coverage decreases wage inequality within an industry (Western and Rosenfeld 2011) and reduces job assignment and wage disparities (Kalleberg, Reskin, and Hudson 2000). We define a state as highly unionized if more than 15% of the state's workers are members of unions. We identified 13 highly unionized states based on the Bureau of Labor Statistics' 2016 economic news release, "Union affiliation of employed wage and salary workers by state."[3]

Results

The results in Table 5 present the odds ratios of not responding to the ATUS for *both* males and females and for *only* males. In general, *both* non-Hispanic Black males and females and *just* non-Hispanic Black males are more likely to be non-respondents in the ATUS than are non-Hispanic White males and White females. As panel A of Table 5 indicates, once we control for home characteristics, human capital, geography, and year fixed effects, non-Hispanic Blacks are still significantly more likely than non-Hispanic Whites to be non-respondents in the ATUS. The results are consistent when we analyze only males. Therefore, in addition to applying ATUS weights in the rest of the analysis, we use the inverse probability of non-response (Non-Response Weight) as one of the other weights.

Next, we compare the mean differences in η between non-Hispanic Black males and non-Hispanic White males across varied weights and under diverse assumptions and present the results in Table 6. The order of the columns in Table 6 is H-G-B estimation, unweighted, weighted by ATUS weight, weighted by Non-Response Weight, weighted by the interaction of ATUS weight and Non-Response Weight, an ATUS weighted specification in which the assumed one-minute non-work activity is allowed, and an

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[3]See https://www.bls.gov/news.release/union2.t05.htm. The highly unionized states are Alaska, California, Connecticut, Hawaii, Illinois, Michigan, Minnesota, Nevada, New Jersey, New York, Oregon, Rhode Island, and Washington.

Table 4. Descriptive Statistics for Individuals Who Have Records in Time Share of Non-Work Activity (η) at Workplace, Non-Self-Employed Males, ATUS (2003 to 2015)

	White Non-Hispanic	Black Non-Hispanic
	Mean	*Mean*
	[SD]	*[SD]*
Time share of no work at work	0.0642	0.0749
	[0.1262]	[0.1276]
Age	42.1492	42.9445
	[12.6692]	[13.1881]
Single parent	0.0209	0.0280
	[0.1430]	[0.1649]
Rent house with cash	0.1968	0.4337
	[0.3976]	[0.4957]
Living in metro area	0.7996	0.8853
	[0.4003]	[0.3187]
Less than high school	0.0610	0.1004
	[0.2393]	[0.3006]
GED	0.0239	0.0237
	[0.1529]	[0.1522]
High school	0.2424	0.2994
	[0.4285]	[0.4581]
Some college	0.1845	0.2190
	[0.3879]	[0.4136]
Associate's degree	0.1050	0.1046
	[0.3065]	[0.3061]
Bachelor's degree	0.2431	0.1749
	[0.4290]	[0.3800]
Master's and above	0.1401	0.0779
	[0.3471]	[0.2681]
Native-born	0.9612	0.8556
	[0.1932]	[0.3516]
Naturalized citizen	0.0191	0.0695
	[0.1369]	[0.2543]
Not a citizen	0.0197	0.0750
	[0.1391]	[0.2634]
Ever married	0.7656	0.6133
	[0.4236]	[0.4871]
Hourly paid jobs	0.5044	0.6404
	[0.5000]	[0.4800]
Private sector	0.8445	0.7920
	[0.3624]	[0.4059]
Part-time worker	0.0872	0.1190
	[0.2821]	[0.3239]
Union member	0.1405	0.1681
	[0.3475]	[0.3741]

Notes: The number of observations for White non-Hispanic is 15,661; the number of observations for Black non-Hispanic is 2,361. ATUS, American Time Use Survey; SD, standard deviation.

ATUS weighted specification that includes non-zero reporters on the non-work activities. As illustrated by Figure 2, the seemingly arbitrary data manipulation in column (6) simply recognizes the possibility of measurement

Table 5. Odds Ratio of Non-Response in the ATUS (2003 to 2015)

	Odds ratio (1)	Odds ratio (2)	Odds ratio (3)
Panel A: Both males and females			
Black non-Hispanic	1.7280***	1.6128***	1.3978***
	(0.0168)	(0.0167)	(0.0149)
No phone		1.9009***	1.6584***
		(0.0420)	(0.0373)
Phone in house, not available		1.6071***	1.4668***
		(0.0805)	(0.0743)
Housing status (rent)			1.4766***
			(0.0139)
Human capital controls	No	No	Yes
Geographic controls	No	Yes	Yes
Time controls	No	Yes	Yes
Panel B: Males			
Black non-Hispanic	1.7278***	1.5940***	1.3654***
	(0.0262)	(0.0254)	(0.0225)
No phone		2.0256***	1.7509***
		(0.0658)	(0.0578)
Phone in house, not available		1.4536***	1.3258***
		(0.1026)	(0.0950)
Housing status (rent)			1.4569***
			(0.0209)
Human capital controls	No	No	Yes
Geographic controls	No	Yes	Yes
Time controls	No	Yes	Yes

Notes: The number of observations for both males and females is 262,484; the number of observations for males only is 122,326. Robust standard errors in parentheses. ATUS, American Time Use Survey. *Statistically significant at the .10 level; ** at the .05 level; *** at the .01 level.

error. It places a lower bound on true effort shirking as one minute. Except for column (7), the specification includes all zero reporters.

In general, we are able to replicate the H-G-B raw results, showing a gap of approximately 7 to 21% in η_{it} between Whites and Blacks. The Black and White racial difference is smallest when we exclude the zero-minute reporters and differs by only one-third from the H-G-B result. The largest differences come from the estimates with the interaction of ATUS weight and Non-Response Weight, which are still close to the H-G-B result. The raw patterns of Black and White racial differences do not account for the differences among other correlated characteristics. We report the parameter estimates of η_{it} on various specifications in Table 7.[4]

We control for educational levels, occupations, and industries and include the state fixed effects in all of the specifications. In addition, we add the surveyed month and the day of the week as covariates to reduce variations from the time diary itself. Further, we add year and metropolitan

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[4]We report only parameter estimates for the binary race indicator for males in Table 7. The full regressions are available upon request.

Table 6. Racial Differences in Time Share of Non-Work Activity (η) at Workplace, Non-Self-Employed Males, ATUS (2003 to 2015)

	(1) H-G-B means	(2) Darity et al. means	(3) Darity et al. means	(4) Darity et al. means	(5) Darity et al. means	(6) Darity et al. means	(7) Darity et al. means
%$\Delta\eta$=	22.95	16.67	20.25	16.85	20.44	18.98	6.93
Black non-Hispanic	0.0793	0.0749	0.0760	0.0749	0.0760	0.0771	0.0967
White, non-Hispanic	0.0645	0.0642	0.0632	0.0641	0.0631	0.0648	0.1034
ATUS weights	Yes	No	Yes	No	Yes	Yes	Yes
Non-response weights	No	No	No	Yes	Yes	Yes	No
Assuming at least 1 minute on non-work activities	No	No	No	No	No	Yes	No
Excluding 0-minute reporters on non-work activities	No	No	No	No	No	No	Yes

Notes: ATUS, American Time Use Survey; Table 1 in H-G-B (Hamermesh, Genadek, Burda 2019).

Table 7. Estimated Racial Differences in Time Share of Non-Work Activity (η) at Workplace, Non-Self-Employed Males, ATUS (2003 to 2015)

	(1) H-G-B dummy variable model	(2) Dummy variable model	(3) Dummy variable model	(4) Dummy variable model	(5) Two-part model	(6) Oaxaca model	(7) Oaxaca model	(8) Censored Tobit model	(9) Log-linear model
%$\Delta\eta$=	11.78	9.46	4.21	3.74	0.16	11.08	11.09	0.46	3.6
Coefficient on Black non-Hispanic	0.0076***	0.0061*	0.0027	0.0024	0.0001	0.007** (unexplained)	0.007** (unexplained)	0.0003***	0.0345
ATUS weights	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Yes
Non-response weights	No	No	Yes	Yes	No	No	Yes	Yes	Yes
Censoring on non-work mins	No	No	No	No	No	No	No	Yes	No
Time fixed effects (year)	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Metro area fixed effects	Yes	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Selection on response probability	No	No	No	No	Yes	No	No	No	No

Notes: We list the coefficient on Black non-Hispanic male in the specification that controls for union and detailed industry and occupation indicators from Table 2 of the H-G-B article (Hamermesh, Genadek, and Burda 2019). ATUS, American Time Use Survey.
*Statistically significant at the .10 level; ** at the .05 level; *** at the .01 level.

fixed effects in specification (4) to allow for the existence of unobserved heterogeneity in shirking preferences that are determined by years and labor markets. For all sub-specifications, we include as controls all of the other covariates summarized in Table 4. Making our results comparable to the result from the H-G-B, we list their specifications in column (1) and our estimates in column (2) to column (9).

In general, the effect of being a non-Hispanic Black male has a positive but statistically insignificant effect, and the coefficients on the non-Hispanic Black indicator across models are within a range of approximately 0.01% and 0.7%. Our estimates from the dummy variable method are approximately between one-third and two-thirds of the value estimated by H-G-B.

This finding suggests that Black–White male differences in the fraction of the worktime spent not working potentially are not large enough to explain, even partially, the Black–White wage gap. Our 0.7% estimates, the largest estimates from our specification, imply that for a 50-week work year, in which the work day is eight hours, compared to a non-Hispanic White male who works 2,000 hours, a non-Hispanic Black male would work approximately 1,980 hours. In the absence of any labor market wage/earnings discrimination, this would translate into a Black–White wage/earnings ratio of approximately 99%, or practically parity. Still, the potential wage effects of time at work not working are ambiguous. Of course, these calculations assume that a 1% reduction in time at work not working reduces wages by 1%. On one hand, if time at work not working is disruptive, the wage effect could be larger. On the other hand, if workers come back refreshed, the effect could be less negative or even positive. So the effect of time at work not working on wages may differ from a simple percentage reduction equal to the percentage of time lost.

If we make a reasonable assumption that ATUS respondents are reporting falsely and/or in error spending zero time at work not working, and put a lower bound of 1 minute on actual shirking in the population of workers, the results in columns (5) and (8) of Table 7 are instructive. In the two-part model of column (5), no statistically significant difference in η_{it} is evident between non-Hispanic White males and non-Hispanic Black males, while the magnitude of difference in η_{it} is smaller as well. At the same time, as a test of the false report of zero minutes at work not working, column (8) reports Tobit parameter estimates to account for the unequal sampling probability for each observation depending on whether the latent dependent variable fell above or below our constructed threshold of unity. The Tobit estimation yields a statistically significant estimate, but the magnitude of that effect amounts to only a 0.03% difference. This small difference does not provide meaningful support of racial disparity in non-working time at the workplace. These two specifications suggest that if a respondent's self-reporting of η_{it} is false, or measured with error, there may be no differences in η_{it} between non-Hispanic White males and non-Hispanic Black males that can explain, even in part, Black–White male wage/earnings disparities.

An alternative way to estimate racial differences in non-work time at the workplace is Blinder-Oaxaca decomposition (Blinder 1973; Oaxaca 1973; Cotton 1988; Oaxaca and Ransom 1994). The Blinder-Oaxaca decomposition technique splits the mean differences between Blacks and Whites in non-work time at the workplace into the portion explained by the characteristics and the portion explained by the treatment, namely returns to those characteristics, such as discrimination. Blinder-Oaxaca decomposition gives a measure from a partial equilibrium perspective of how large the gap would be if Blacks and Whites had similar characteristics or if Blacks had the same level of returns as Whites. Columns (6) and (7) of Table 7 present the coefficients on the treatment or unexplained portion. Among the total mean differences between Black and White workers (0.0128), 0.007 is explained by the treatment or discrimination, which is 55% of the total gap. If we want to tie the racial differences in non-work time back to the wage gap, as suggested by the H-G-B result, then racial difference in non-work at the work site can explain up to 10% of the adjusted wage gap between minority and non-Hispanic White workers; the unexplained gap will account for at least half of the wage gap.

Finally, we summarize in the first row of Table 7 all of the results across the various models, focusing on the percentage differences in η_{it} between Blacks and Whites. The H-G-B regression models report gaps of approximately 12%, and our regression models report gaps between 4 and 10%. Although we can replicate these results, the estimated coefficients are not statistically significant in our replication models. When we adjust for non-response bias and control for time and location fixed effects, the gap declines to approximately 4% (model (4)). These lower amounts are not statistically significant.

The parameter estimates in Table 7 could be biased, as the specifications might be sensitive to lower and upper bounds on time spent on non-work, even in the cases in which controls are censoring on non-work minutes. To robustly estimate the relative effects of being a non-Hispanic Black male on time spent in non-work activity, Table 8 reports results from unconditional quantile regression specifications. In columns (1) to (6), we report fixed effects unconditional quantile regression (UQR) parameter estimates (Firpo, Fortin, and Lemieux 2009) for our dummy variable specifications in column (4) of Table 7. Relative to conditional quantile parameter estimates, UQR treatment parameter estimates are also free of the heterogeneity associated with quantile-specific non-treatment covariates, as UQR parameter estimates are marginalized across the distribution of other covariates in the specification (Borah and Basu 2013). In columns (7) and (8) of Table 8, we report UQR parameter estimates for the dummy variable specifications without fixed effects (Powell, Baker and Smith 2014; Baker 2016) to cohere with the parameter estimates in columns (2) and (3) of Table 7. For all specifications, we report UQR parameter estimates for the 0.50 quantile, which constitutes the middle of the distribution when possible outliers are

at the lower and/or upper bounds of the distribution (Borgen 2016). Similar to the parameter estimates in Table 7, the fixed effects are conditioned on year and metropolitan area, and with and without the ATUS and non-response weights.

Across all the UQR parameter estimates in columns (1) to (6) of Table 8, the estimated coefficients on Black non-Hispanic males are approximately similar. As these are unconditional quantile parameters, evaluated at the median, they capture the treatment effect of being Black non-Hispanic males on non-work activity, without conditioning the quantile on control variables. For the UQR parameter estimates without fixed effects in columns (7) and (8) of Table 8, their smaller magnitude coheres with the pattern in columns (2) and (3) in Table 7, whereby our estimates relative to those of H-G-B are smaller. This outcome suggests that in general, our parameter estimates in columns (2) to (9) of Table 7 are not sensitive to outliers in the ATUS data at the lower and upper bounds and are robust. As the specifications include the same dummy variables for our specifications in columns (2) to (4) of Table 7, the approximate similarity of the parameter estimates in Table 8 also suggests that our estimated treatment effects of Black non-Hispanic males on non-work activity reported in Table 7 are not conditional and that they capture robust population treatment effects.

We conclude that the H-G-B results are not robust across alternative model specifications that make reasonable adjustments for both response and non-response biases.

Conclusion

This article considers the extent to which non-Hispanic Black males, a group that has experienced persistent wage/earnings disparities relative to non-Hispanic White males, spend relatively more time not working while on the job than do non-Hispanic White males. We estimate specifications of time spent on non-work activities at work with data on non-Hispanic Black and non-Hispanic White males from the 2003 to 2015 American Time Use Survey. Our parameter estimates reveal small, statistically significant differences between unadjusted measures of time spent not working among non-Hispanic Black and non-Hispanic White males. We demonstrate, however, that these small differences disappear entirely when imposing a lower bound on time reported as not working by respondents, a method that accounts for false and/or erroneous reporting when respondents claim they spent zero time at work not working. An implication of our findings is that non-Hispanic Black–White male differences in the fraction of the workday spent not working either are not large enough to partially explain the Black–White wage gap, or simply do not exist at all.

Taking the Hamermesh, Genadek, and Burda (2017, 2019) findings seriously, an analyst might conclude that Black men actually work harder than White men—that is, at greater intensity—during the more limited time they

are devoting to work on the job. None of the administrative or survey data enable us to separate hours paid for work from actual hours working at work. Blacks may take longer "breaks" because they require more recovery time from a more intense work pace. Moreover, it is also plausible that Black workers could spend more time at work not working, not because they are lazy, but because they are incredibly productive, finish their tasks in shorter amounts of time, and thus, have more time to spend on non-work-related activities. Thus, the line between time spent not working and alleged laziness is an arbitrary line in empirical tests and our findings do not support this claim. Besides, employers assign different positions and responsibilities to Black and White workers (Stauffer and Buckley 2005) and employee perceptions of discrimination could change their beliefs about the quality of the job (Goldsmith, Sedo, Darity, and Hamilton 2004), which may introduce a difference in the non-work time. Within labor demand, this dispositional job assignment, as unobservable to scholars, can influence the racial differences in non-work time and affect the disparity in employment and wages. Glover, Pallais, and Pariente (2017) found that because of discrimination and prejudiced managers, minority workers provide suboptimal work effort. According to this reasoning, when minority workers work with unbiased managers, they perform significantly better than their majority counterparts.

Focusing on all males, including zero earners and non-respondents, other studies contribute to our understanding of the racial gap in earnings by looking into differences in the earnings distribution (Darity and Myers 1998; Chandra 2000; Bayer and Charles 2018; Bollinger, Hirsch, Hokayem, and Ziliak 2019). The rising overall earnings inequality (Darity 2005; Autor, Katz, and Kearney 2008) has differentially affected the labor market outcomes for males at varying points in the distribution. Therefore, ignoring labor market non-participation and survey non-response may *understate* racial inequality in the labor market. One can explore other dimensions of the non-work activities that might affect racial gaps in time use but we find that the non-response bias overwhelms the results provided by Hamermesh et al. (2017, 2019). With the public use data, we are limited in our assessment to the direction and magnitude of bias from the ATUS item non-response and non-response rates. Given that Blacks represent a relatively small share in the ATUS, however, the resulting estimates are noisier, producing the statistically insignificant results we report in this article.

Our results suggest no empirical support for the notion that Blacks, relative to Whites, are lazier workers or spend less time at work working. As such, alleged relative Black laziness is nothing more than a historic stereotype that can serve, at a minimum, to inframarginally allocate Black workers to jobs in which shirking is relatively easier, which would rationalize a racially disparate distribution of rewards associated with employment (Embrick and Henricks 2013; Lahiri 2018). The previously untested

Table 8. Unconditional Quantile Parameter Estimates: Racial Differences in Time Share of Non-Work Activity (η) at Workplace, Non-Self-Employed Males, ATUS (2003 to 2015)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Coefficient on Black non-Hispanic	0.0069***	0.0074***	0.0071***	0.0076***	0.0069***	0.0076***	0.0067***	0.0067***
ATUS weights	No	No	Yes	Yes	No	No	Yes	No
Non-response weights	No	No	No	No	Yes	Yes	No	Yes
Censoring on non-work minutes	No	No	No	No	No	No	No	No
Time fixed effects (year)	Yes	No	Yes	No	Yes	No	No	No
Metro area fixed effects	No	Yes	No	Yes	No	Yes	No	No

Notes: ATUS, American Time Use Survey.
*Statistically significant at the .10 level; ** at the .05 level; *** at the .01 level.

hypothesis that the unobserved portion of the racial disparity in wages is related to lack of work effort is unsupported.

Finally, to the extent that stereotypes about Black laziness on the job constitute a "stereotype threat" (Steele and Aronson 1995) for Black workers, they can impose costs on Black workers (e.g., anxiety and stress in response to perceptions of being lazy), potentially undermining work performance (McGee 2018) and causing their productivity at work to fall relative to Whites. Our findings suggest that empirically, and with respect to how Blacks may respond to stereotypes about being unproductive relative to Whites and other non-Blacks, for Black workers there is no stereotype threat effect with respect to effort at work. In this context, our findings suggest that the Stepin Fetchit hypothesis, which is a popular reification of the idea and stereotype that Blacks are relatively lazy, does not appear to be operative in the overall labor market.

References

Autor, David H., Lawrence F. Katz, and Melissa S. Kearney. 2008. Trends in US wage inequality: Revising the revisionists. *Review of Economics and Statistics* 90(2): 300–323.

Baker, Matthew. 2016. GENQREG: Stata module to perform Generalized Quantile Regression. *Statistical Software Components* S458158, Boston College Department of Economics.

Bartos, Vojtech, Michal Bauer, Julie Chytilova, and Filip Matejka. 2016. Attention discrimination: Theory and field experiments with monitoring information acquisition. *American Economic Review* 106(6): 1437–75.

Bayer, Patrick, and Kerwin Kofi Charles. 2018. Divergent paths: A new perspective on earnings differences between black and white men since 1940. *Quarterly Journal of Economics* 133(3): 1459–1501.

Bell, Linda A. 1998. Differences in work hours and hours preferences by race in the US. *Review of Social Economy* 56(4): 481–500.

Blinder, Alan S. 1973. Wage discrimination: Reduced form and structural estimates. *Journal of Human Resources* 8(4): 436–55.

Bollinger, Christopher R., Barry T. Hirsch, Charles M. Hokayem, and James P. Ziliak. 2019. Trouble in the tails? What we know about earnings nonresponse 30 years after Lillard, Smith, and Welch. *Journal of Political Economy* 127(5): 2143–85.

Borah, Bijan J., and Anirban Basu. 2013. Highlighting differences between conditional and unconditional quantile regression approaches through an application to assess medication adherence. *Health Economics* 22(9): 1052–70.

Borgen, Nicolai T. 2016. Fixed effects in unconditional quantile regression. *Stata Journal* 16(2): 403–15.

Bushway, Shawn, Brian D. Johnson, and Lee Ann Slocum. 2007. Is the magic still there? The use of the Heckman two-step correction for selection bias in criminology. *Journal of Quantitative Criminology* 23(2): 151–78.

Chandra, Amitabh. 2000. Labor-market dropouts and the racial wage gap: 1940–1990. *American Economic Review* 90(2): 333–38.

Clark, Kim B. 1980. The impact of unionization on productivity: A case study. *Industrial and Labor Relations Review* 33(4): 451–69.

Coleman, Major G. 2003. Job skill and black male wage discrimination. *Social Science Quarterly* 84(4): 892–906.

Cotton, Jeremiah. 1988. On the decomposition of wage differentials. *Review of Economics and Statistics* 70(2): 236–43.

Darity, William A., Jr. 2005. Stratification economics: The role of intergroup inequality. *Journal of Economics and Finance* 29(2): 144–53.

Darity, William A., Jr., Darrick Hamilton, and James B. Stewart. 2015. A tour de force in understanding intergroup inequality: An introduction to stratification economics. *Review of Black Political Economy* 42(1-2): 1–6.

Darity, William. A., Jr., and Samuel L. Myers 1998. *Persistent Disparity: Race and Economic Inequality in the United States since 1945.* Cheltenham, UK: Edward Elgar Publishing.

Davis, John B. 2014. Stratification economics and identity economics. *Cambridge Journal of Economics* 39: 1215–29.

DeSante, Christopher D. 2013. Working twice as hard to get half as far: Race, work ethic, and America's deserving poor. *Journal of Political Science* 57(2): 342–56.

Embrick, David G., and Kasey Henricks. 2013. Discursive colorlines at work: How epithets and stereotypes are racially unequal. *Symbolic Interaction* 36(2): 197–215.

Firpo, Sergio, Nicole M. Fortin, and Thomas Lemieux. 2009. Unconditional quantile regressions. *Econometrica* 77(3): 953–73.

Freeman, Richard B., and James L. Medoff. 1984. *What Do Unions Do?* New York: Basic Books.

Frondel, Manuel, and Colin James Vance. 2012. Interpreting the outcomes of two-part models. *Applied Economics Letters* 19(10): 987–92.

Glover, Dylan, Amanda Pallais, and William Pariente. 2017. Discrimination as a self-fulfilling prophecy: Evidence from French grocery stores. *Quarterly Journal of Economics* 132(3): 1219–60.

Goldsmith, Arthur H., Stanley Sedo, William A. Darity Jr., and Darrick Hamilton. 2004. The labor supply consequences of perceptions of employer discrimination during search and on-the-job: Integrating neoclassical theory and cognitive dissonance. *Journal of Economic Psychology* 25(1): 15–39.

Hamermesh, Daniel S., Katie R. Genadek, and Michael C. Burda. 2017. Racial/ethnic differences in non-work at work. NBER Working Paper No. 23096. Cambridge, MA: National Bureau of Economic Research.

———. 2019. Racial/ethnic differences in non-work at work. *ILR Review* 74(2): 272–92.

Heckman, James J. 1979. Sample selection bias as a specification error. *Econometrica* 47(1): 153–61.

Hofferth, Sandra L., Sarah M. Flood, Matthew Sobek, and Daniel Backman. 2020. American Time Use Survey data extract builder: Version 2.8 [dataset]. College Park, MD: University of Maryland and Minneapolis, MN: IPUMS. Accessed at https://doi.org/10.18128/D060.V2.8.

Hurst, Roy. 2006. Stepin Fetchit, Hollywood's first Black film star. NPR, March 6. Accessed at https://www.npr.org/templates/story/story.php?storyId=5245089.

Kalleberg, Arne L., Barbara F. Reskin, and Ken Hudson. 2000. Bad jobs in America: Standard and nonstandard employment relations and job quality in the United States. *American Sociological Review* 65(2): 256–78.

Kim, Jae Kwang, and Jay J. Kim. 2007. Nonresponse weighting adjustment using estimated response probability. *Canadian Journal of Statistics* 35(4): 501–14.

Kuhn, Peter, and Fernando Lozano. 2008. The expanding workweek? Understanding trends in long hours among U.S. men, 1979–2006. *Journal of Labor Economics* 26(2): 311–43.

Lahiri, Bidisha. 2018. Racial earnings disparities with endogenous labor market participation. *Journal of Economics, Race, and Policy* 1(1): 16–25.

Mason, Patrick L. 1999. Male interracial wage differentials: Competing explanations. *Cambridge Journal of Economics* 23(3): 261–99.

———. 2004. NEA presidential address: Identity, markets, and persistent racial inequality. *Review of Black Political Economy* 32(1): 13–36.

McGee, Ebony. 2018. "Black genius, Asian fail": The detriment of stereotype lift and stereotype threat in high-achieving Asian and Black STEM students. *American Educational Research Association (AERA) Open* 4(4): 1–16.

McKay, Patrick F., and Michael A. McDaniel. 2006. A reexamination of black-white mean differences in work performance: More data, more moderators. *Journal of Applied Psychology* 91(3): 538–54.

Moffitt, Robert A. 1999. New developments in econometric methods for labor market analysis. In Orley C. Ashenfelter and David Card (Eds.), *Handbook of Labor Economics*, Vol. 3, pp. 1367–97. Amsterdam: North-Holland.

Neumark, David, and Judith Rich. 2019. Do field experiments on labor and housing markets overstate discrimination? A re-examination of the evidence. *ILR Review* 72(1): 223–52.

Oaxaca, Ronald. 1973. Male-female wage differentials in urban labor markets. *International Economic Review* 14(3): 693–709.

Oaxaca, Ronald L., and Michael R. Ransom. 1994. On discrimination and the decomposition of wage differentials. *Journal of Econometrics* 61(1): 5–21.

Pager, Devah, and Hana Shepherd. 2008. The sociology of discrimination: Racial discrimination in employment, housing, credit, and consumer markets. *Annual Review of Sociology* 34: 181–209.

Pencavel, John. 2016. Whose preferences are revealed in hours of work? *Economic Inquiry* 54(1): 9–24.

Powell, David, Matthew Baker, and Travis Smith. 2014. Generalized quantile regression in Stata. 2014 Stata Conference 12, Stata Users Group.

Puhani, Patrick. 2000. The Heckman correction for sample selection and its critique. *Journal of Economic Surveys* 14(1): 53–68.

Reyna, Christine. 2000. Lazy, dumb, or industrious: When stereotypes convey attribution information in the classroom. *Educational Psychology Review* 12(1): 85–110.

Ross, Stephen L., and Yves Zenou. 2008. Are shirking and leisure substitutable? An empirical test of efficiency wages based on urban economic theory. *Regional Science and Urban Economics* 38(5): 498–517.

Scharfstein, Daniel O., Andrea Rotnitzky, and James M. Robins. 1999. Adjusting for nonignorable drop-out using semiparametric nonresponse models. *Journal of the American Statistical Association* 94(448): 1096–120.

Stauffer, Joseph M., and M. Ronald Buckley. 2005. The existence and nature of racial bias in supervisory ratings. *Journal of Applied Psychology* 90(3): 586–91.

Steele, Claude M., and Joshua Aronson. 1995. Stereotype threat and the intellectual test performance of African Americans. *Journal of Personality and Social Psychology* 69: 797–811.

Stolzenberg, Ross M., and Daniel A. Relles. 1990. Theory testing in a world of constrained research design: The significance of Heckman's censored sampling bias correction for nonexperimental research. *Sociological Methods & Research* 18(4): 395–415.

Van Ommeren, Jos N., and Eva Gutiérrez-i-Puigarnau. 2011. Are workers with a long commute less productive? An empirical analysis of absenteesim. *Regional Science and Urban Economics* 41(1): 1–8.

Western, Bruce, and Jake Rosenfeld. 2011. Unions, norms, and the rise in US wage inequality. *American Sociological Review* 76(4): 513–37.

Wooldridge, Jeffrey M. 2007. Inverse probability weighted estimation for general missing data problems. *Journal of Econometrics* 141(2): 1281–301.