1. Methods
   1. Data and analysis overview

The GSS is a nationally representative survey of non-institutionalized adults ages 18 and older, which has been conducted biennially since 1994.1 All GSS survey waves since 1975 have used full-probability sampling.1 Before 2006, GSS excluded Spanish speakers from the target population; however, since 2006, Spanish speakers have been included.1 In 2002, 2006, 2010, 2014, and 2018, GSS administered the Quality of Worklife (QWL) module to capture how working conditions have changed temporally.1 The GSS conducts most interviews in-person.1

Our sample included respondents to the QWL survey waves who identified as working fulltime, working parttime, or temporarily not working; the GSS did not administer the QWL to other respondents.1 We excluded all respondents on survey ballot “d”, as well as 2002 respondents on survey ballot “b”, as they were not administered the QWL module either.1 Additionally, 12% of respondents from the 2006 and 2014 surveys stopped their interviews prior to completing the QWL module; we also excluded them from our sample.2 Our final sample included 6,806 respondents.

We conducted our analyses using R version 4.0.2.3 We weighted all our estimates to make them nationally representative,1 and we accounted for the GSS’s complex survey design in our standard error estimates using Taylor series linearization.1,4 Our R code is on Github (link); GSS data is publicly available (gss.norc.org).

* 1. Measures
     1. Social class

We based our four-category class measure on Wright’s neo-Marxist class theory5,6 and on prior GSS class analyses.7–9 Figure 1 displays how we allocated respondents into classes. Workers were those who did not supervise others, who were not self-employed, and who did not have a “chief executive” occupation (2010 census occupation code). Second, managers were those who did supervise others, who were not self-employed, and who did not have a “chief executive” occupation. Third, the petite bourgeoisie were those who did not supervise others, but who were self-employed or had a “chief executive” occupation. Finally, capitalists were those who did supervise others, and who were self-employed or had a “chief executive” occupation. We classified CEOs as petite bourgeoisie or capitalists because they often own considerable productive property (e.g., stocks); furthermore, CEO-capitalists, like other capitalists, may appropriate and distribute the value produced by workers’ labor.5

* + 1. QWL measures

We analyzed 16 QWL variables, which we allocated into four categories. Respondents responded to most QWL variables using Likert scales (e.g., strongly agree, agree, disagree, strongly disagree); to increase interpretability of our estimates and reduce sparse cells, we transformed the scales into binary responses (e.g., strongly agree or agree versus disagree or strongly disagree). The 16 variables and four categories were as follows:

* Compensation and safety: dissatisfied with job; income alone does not pay bills; poor safety conditions; safety not a priority.
* Labor process: repetitive work tasks; do not learn new things; face conflicting demands; need to work fast.
* Autonomy: do not take part in decisions; lack freedom; mandatory to work extra hours; cannot change schedule on daily basis (not administered in the 2018 GSS wave).
* Conflict: bad worker-management relations; do not trust management; not treated with respect; face racism, sexism, sexual harassment, ageism, or other forms of discrimination or harassment.

Appendix AX contains the exact wording for the relevant survey questions and responses.

* + 1. Covariates

Covariates of interest included respondents’ age, self-identified race/ethnicity, gender, education, census region of residence, family income, self-rated health (SRH), and days of poor mental health in the past 30 days. Table 1 displays variable categories.

* 1. Statistical analyses

First, we characterized the demographic, socioeconomic, and health composition of each class in our sample by calculating descriptive statistics of the covariates of interest, stratified by class.

Second, we estimated class inequities in QWL. Specifically, for each QWL variable, we estimated the prevalence of the adverse condition among each class relative to the prevalence among workers (i.e., prevalence ratios) using log-linear Poisson models10 adjusted for age and year, which we specified as three-knot restricted cubic splines to allow for nonlinear confounder-outcome relationships.11 We did not adjust the models for other covariates to capture the total magnitude of class inequities in QWL.

Third, we estimated class-by-gender and class-by-race in inequities in QWL. Specifically, for each QWL variable, we estimated the prevalence of the adverse condition among each class-gender or class-race relative to the prevalence among male workers or non-Hispanic (NH) white workers by including class-by-gender or class-by-race interaction terms in the log-linear Poisson models. Due to small cell sizes, in the class-by-race analyses we categorized race as NH white versus person of color (POC; Hispanic or NH Black); we excluded those identifying as NH other because of the group’s heterogeneity.

Finally, we examined gender-by-race inequities in QWL within the working class. Specifically, we first restricted our sample to respondents classified as “workers”. Next, for each QWL variable, we estimated the prevalence of the adverse condition among each gender-race relative to the prevalence among NH white men by including gender-by-race interaction terms in the log-linear Poisson models. Again, we categorized race as NH white versus person of color (Hispanic or NH Black) and excluded those identifying as NH other.

* + 1. Missing data

Most variables analyzed contained some unplanned missingness (class measure: 1% missing; QWL variables: <4% missing; covariates: <8% missing). To address the missingness, we used multiple imputation by chained equations with 20 replications and 25 iterations;12 we assumed missing values were missing at random conditional on measured covariates.13 We combined the estimates and standard errors from analyzes of the 20 multiply-imputed datasets using Rubin’s Rules.12,13 Estimates and standard errors from complete-case analyses were similar.

1. Results
   1. Descriptive statistics

Across survey waves, 55% of respondents were workers, 31% were managers, 8% were petty bourgeoisie, and 6% were capitalists (Table 1); nonetheless, while just 47% of NH white men were workers, 59% of NH white women, 58% of POC men, and 63% of POC women were workers (Appendix AX). Thus, relative to other classes, workers were more often women and racially-minoritized; they also tended to be less-educated and lower-income. Meanwhile, managers tended to be more educated and have higher incomes than the petty bourgeoisie, although they were otherwise demographically similar. Finally, relative to other classes, capitalists were more likely to be men and NH white, and they tended to be more educated and have greater incomes. Regarding health, workers and the petit bourgeoisie tended to report worse SRH than others, particularly relative to capitalists; workers also tended to report worse mental health than others.

* 1. Regression analyses
     1. Class, class-by-gender, and class-by-race inequities in QWL

We identified large class, class-by-gender, and class-by-race inequities in QWL. Regarding our compensation and safety measures,

Regarding our labor process measures,

Regarding our autonomy measures,

Finally, regarding our conflict measures,

* + 1. Gender-by-race inequities in QWL within working class

We also identified modest gender-by-race inequities in QWL within the working class. Regarding our compensation and safety measures,

Regarding our labor process measures,

Regarding our autonomy measures,

Finally, regarding our conflict measures,

note weirdness about wkdecide

Bibliography

1. Smith TW, Davern M, Freese J, Morgan SL. *General Social Surveys, 1972-2018 [Machine-Readable Data File]*. NORC; 2019:1 data file (64,814 logical records) and 1 codebook (3,758 pp).

2. Email correspondence with GSS help desk in December, 2020 (issue number 6557).

3. R Core Team. *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing; 2020. https://www.R-project.org/

4. Lumley T. *Package “Survey.”* Accessed March 18, 2021. https://cran.r-project.org/web/packages/survey/survey.pdf

5. Wright EO. Understanding class: towards an integrated analytical approach. *New Left Rev*. 2009;60(Nov/Dec):101-116.

6. Wright EO. *Class Counts: Comparative Studies in Class Analysis. New York: Cambridge University Press.* Cambridge University Press; 1997.

7. Eisenberg-Guyot J, Prins SJ. Relational social class, self-rated health, and mortality in the United States. *Int J Health Serv*. 2020;50(1):7-20. doi:10.1177/0020731419886194

8. Wodtke GT. Continuity and change in the American class structure: qorkplace ownership and authority relations from 1972 to 2010. *Res Soc Stratif Mobil*. 2015;42:48-61. doi:10.1016/j.rssm.2015.07.002

9. Wodtke GT. Social relations, technical divisions, and class stratification in the United States: an empirical test of the death and decomposition of class hypotheses. *Soc Forces*. 2017;95(4):1479-1508. doi:10.1093/sf/sox012

10. Spiegelman D. Easy SAS calculations for risk or prevalence ratios and differences. *Am J Epidemiol*. 2005;162(3):199-200. doi:10.1093/aje/kwi188

11. Harrell FE. *Package “Rms.”* Accessed March 18, 2021. https://cran.r-project.org/web/packages/rms/rms.pdf

12. van Buuren S. *Package “Mice.”* Accessed March 18, 2021. https://cran.r-project.org/web/packages/mice/mice.pdf

13. Rubin DB. *Multiple Imputation for Nonresponse in Surveys*. John Wiley and Sons; 2004.