



Samuel Cole
Graduate Student
Auburn University

Zachary Cowell
Graduate Student
Auburn University

John M. Nunley, Ph.D.
Professor
University of Wisconsin – La Crosse

R. Alan Seals, Jr., Ph.D.
Associate Professor
Auburn University

The Changing Task Content of Jobs for Older Workers in the United States

Center for Financial Security

University of
Wisconsin-Madison

1300 Linden Drive
Madison, WI 53706

608-890-0229
cfs@mailplus.wisc.edu
cfs.wisc.edu

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Abstract

With data on occupational task content from O*NET and ORS and survey data from the American Community Survey (ACS) and 1979 National Longitudinal Survey of Youth (NLSY79), we document how the physical, cognitive, routine, and social characteristics of work in the United States have evolved since the early 2000s; examine how the task content of work changes of the lifecycle; and estimate the effects of changing task content on work outcomes. we find that the intensity of routine manual and routine cognitive tasks has risen, since early in 21st century. Workers nearing retirement have experienced declining rates of nonroutine tasks, while routine tasks have risen over time. We find significant racial/ethnic and gender differences in task content over the lifecycle. White and Asian workers tend to work in occupations high in nonroutine cognitive tasks. Hispanic and Black workers, especially men, work in the most physically demanding jobs over their entire working lives. we find the largest earnings gains are associated with higher nonroutine cognitive analytical, nonroutine cognitive interpersonal, and social skill tasks. Workers who worked in an occupation in 2004 with high cognitive analytical task intensity were out of the labor force less, while those employed in an occupation with high nonroutine manual physical tasks were out of the labor force more.

Key words: worker tasks, old age labor supply, earnings, employment, race/ethnicity, gender

JEL Categories: J1, J2, J3, H5

1. Introduction

The nature of work in the United States has undergone a dramatic transformation since the 1970s. Researchers have documented rising inequality as a result of complementarities between technological change and high-skilled labor (Goldin and Katz 2009), reductions in employment and wages in occupations for which workers repeat tasks (D. Autor and Dorn 2013), declining employment in cognitive-intensive jobs and rising employment in manual-intensive tasks during the 1990s and 2000s (Beaudry, Green, and Sand 2015), and growth in the demand for social skills (Deming 2017). These developments in the labor market were roughly concurrent with a sharp decline in the labor share of income, as the most productive firms accumulated market power (D. Autor et al. 2020) and leveraged the talent of highly skilled workers (Card, Heining, and Kline 2013; Song et al. 2019).

These extensive secular changes in the U.S. economy also coincide with a growing elderly population. By 2026, one out of every four workers will be over the age of 55 (Collins and Casey 2017). Due to the size of the baby boom generation and the expected depletion of the Old-Age and Survivors Insurance (OASI) and Disability Insurance (DI) trust funds around 2035, policymakers will soon need to make substantial changes to the social security system (Shoven, Slavov, and Watson 2021). The expected policy changes to Social Security will likely depend on the expected length of work life, earnings, and assets of cohorts who have not yet reached retirement age. As the largest generation in American history transitions to retirement over the next decade, studying how the requirements of jobs have changed and the impact of such changes on workers as they age is important for Social Security Administration (SSA) policy.

In this study, we document how the mental, physical and social requirements of occupations have changed over time for the aggregate labor market and separately for different age groups. Second, we examine how the task content of work varies with age for different demographic and education groups. Lastly, we measure the impact of the changing task content of work on employment outcomes for a cohort of older workers who are nearing their pensionable ages.

In our analysis, we use a variety of data sources, including the Occupation Information Network (O*NET), the Occupation Requirements Survey (ORS), American Community Survey (ACS), and the 1979 Cohort of the National Longitudinal Survey of Youth (NLSY79). To generate overall and age-specific time trends in the task content of work, we follow Ross (2017) and construct a panel of occupations from the 2004—2019 O*NET surveys. We then combine the O*NET and ACS data sets to produce employment-weighted statistics based on the task measures from Acemoglu and Autor (2011) as well as the extensions made by Deming (2017).

Our analysis of the time trends in worker tasks follows the approaches of Ross (2017) and Atalay et al. (2020), as these studies examine both flows of workers across occupations and changes in tasks within occupations. The second part of our analysis relies on the ACS-O*NET combined data set to examine how the tasks that workers perform vary with age. We supplement the descriptive analysis of the task content of work by combining the 2018 ACS and ORS data sets. The drawback of the ORS is that the survey began in 2018. Therefore, it is not yet suited to study the evolution of worker tasks over a longer time span. However, the ORS has the advantage of providing economically sensible margins, such as hours spent performing a particular task and occupational lifting requirements in pounds required. The final part of the study examines worker responses to changing task content. We rely primarily on the NLSY79, given our ability to follow individual workers over time. Much of our analysis of worker responses focuses on the effect on earnings and labor supply associated with different tasks. The longitudinal nature of the NLSY79 allows us to study how changing task content affects occupation switching within and between firms, as well as the prospect of holding multiple jobs. Apart from Hudomiet and Willis (2021), the literature has not focused on how changes in the task content of jobs affect workers across age groups.

Relative to 2004, routine cognitive and routine manual task intensities increase over time, while nonroutine manual physical tasks rise from 2004 to 2010 but then fall thereafter. The intensity with which workers perform nonroutine cognitive tasks, whether the tasks are analytical or interpersonal, and social skills tasks declines over our sample period. Like Atalay et al. (2020), we show the variation in worker tasks is larger within occupation than it is between occupations.

The results from the ACS pseudo-lifecycle analysis of worker tasks reveals several insights, but perhaps the main takeaway is that men and women, different races/ethnicities, and education groups perform starkly different types of work as age increases. For the ACS cohorts, we find that White men tend to work in jobs with high nonroutine cognitive, analytical, and interpersonal tasks as well as social skill tasks, whereas White women tend to perform more routine cognitive tasks as they age. With respect to race/ethnicity, Hispanic people and Black people work in more physically demanding jobs than White and Asian people as age increases, whereas White people and Asian people work in jobs that demand more cognitive and social skill tasks. For most tasks, there is little variation by age for different education groups. Workers with the most education tend to work in jobs high in nonroutine cognitive tasks—both analytical and interpersonal—and social skill tasks, while workers with the lowest levels of education work in jobs that require both routine and nonroutine manual tasks. Occupations high in routine cognitive tasks tend to employ workers with higher levels of education when they are young, but as these higher education groups age, particularly those with Bachelors or graduate/professional degrees, they transition out of jobs high in routine task content. Workers who disproportionately work in jobs with high routine cognitive task requirements are those with some college education.

From the NLSY79, we estimate the effects of changing task content on different work outcomes. We find the largest earnings gains are associated with higher nonroutine cognitive analytical, nonroutine cognitive interpersonal, and social skill tasks. Workers who worked in an occupation in 2004 with high cognitive analytical task intensity were out of the labor force less, while those employed in an occupation with high nonroutine manual physical tasks were out of the labor force more. Nonroutine cognitive analytical task intensity is negatively associated with occupation switching, particularly for a job with a different employer, whereas nonroutine cognitive interpersonal task intensity is positively related to occupation switching, but the switching tends to occur within the worker's current employer. Workers in jobs with high nonroutine manual physical task intensity were less likely to switch occupations. Changes in task content tend to have little effect on the probability of holding more than one job.

2. Data and Methods

Our analysis is based on three different combinations of data sources: (i) a panel of occupations from the Occupational Information Network (O*NET) linked to pooled cross-sectional data based on the American Community Survey (ACS), (ii) the Occupation Requirements Survey (ORS) linked to the ACS, and (iii) a panel of occupations from O*NET linked to the 1979 Cohort of the National Longitudinal Survey of Youth (NLSY79). Sample construction, variable creation, and information about our analysis is provided in the following subsections.

2.1. Constructing the Panel of Occupations and Task Intensity Measures

We follow Ross (2017, 2020) and create a panel of O*NET characteristics from 2004—2019. We then rely on task definitions from Acemoglu and Autor (2011) and Deming (2017) to examine how the task content of work has changed throughout the 2000s and 2010s. Our work builds on a larger literature investigating how the tasks completed by workers has changed over long periods of time, including Autor, Levy, and Murnane (2003), Autor and Price (2013), and Atalay et al. (2020). We incorporate five task variables from Acemoglu and Autor (2011), including nonroutine cognitive analytical, nonroutine cognitive interpersonal, routine cognitive, routine manual, and nonroutine manual physical task intensity and one from Deming (2017), which measures social skill task intensity. In Table 2.1, we list the task measures, the survey questions used to create them, and the O*NET module from which the questions were taken.

The task intensities are based on the level scale from O*NET. It is a 0—7 scale that measures the degree to which a task/knowledge/skill/ability is required or needed to perform an occupation. We use the level scale in lieu of the importance scale, as it provides

Table 2.1 – Task Intensity Measure Definitions

Task	O*NET Module	Survey Questions
Nonroutine Cognitive Analytical	Work Activities	Analyzing data/information
	Work Activities	Thinking creatively
	Work Activities	Interpreting information for others
Nonroutine Cognitive Interpersonal	Work Activities	Establishing and maintaining personal relationships
	Work Context	Guiding, directing, and motivating others
	Work Context	Coaching/developing others
Routine Cognitive	Work Context	Importance of repeating same tasks
	Work Context	Importance of being exact or accurate
	Work Context	Structured vs. unstructured work (reverse scale)
Routine Manual	Work Activities	Pace determined by speed of equipment
	Work Context	Controlling machines and processes
	Work Context	Spend time making repetitive motions
Nonroutine Manual Physical	Work Activities	Operating vehicles, mechanized devices, or equipment
	Work Context	Spend time using hands to handle, control or feel objects, tools or controls
	Abilities	Manual dexterity
	Abilities	Spatial orientation
Social Skill	Skill	Coordination
	Skill	Negotiation
	Skill	Persuasion
	Skill	Social Perceptiveness

Notes: The first five task measures are taken from Acemoglu and Autor (2011) and the last task measure is taken from Deming (2017).

a better measure of how much a particular task is done for an occupation. As a result, we contend that the level scale is more appropriate for measuring task intensity than the importance scale. Following Autor, Levy, and Murnane (2003) and Deming (2017), we convert the average scores from the survey questions to a 0—10 scale, which reflects their weighted percentile rank in each year.¹

¹ In an effort to streamline the discussion, we have omitted many of the details behind constructing the O*NET panel data set as well as some of the intricacies of the data. One of the main issues is ensuring consistency in the O*NET-SOC codes over the sample period, which requires the use of crosswalks. We will provide data sets, crosswalks, annotated STATA code, and other supporting documentation upon request.

2.2. Linking the Longitudinal Occupation Data to Individual-Level Data Sets

The longitudinal occupation data from O*NET are linked to two other data sets: pooled cross-sectional data from the ACSs and individual-level longitudinal data from the NSLY79. We use the combination of the ACSs and O*NET to construct national trends in the task intensities, age-specific trends in task intensities, and task-intensity-age profiles for different types of workers (e.g., gender, race/ethnicity, education). The combination of the NLSY79 and O*NET is used to examine the labor market consequences associated with changing task intensity for a cohort of workers who are followed from mid- to late-career (40—60 years of age). Information on how these data are linked and some of the key issues associated with linking them is discussed in the following subsections.

2.2.1. ACS-O*NET

Constructing national and age-specific trends in task intensity.

Using the O*NET task measures in isolation could be misleading, as each occupation in the data set would receive equal weight. From the ACS, almost 50 percent of workers are employed in four major occupation groups: office and administration, sales, management, and healthcare practitioners. To account for differences in occupational prevalence, we link the task intensity measures from O*NET to the ACS to produce labor supply weights representative of the US labor market.²

To create the labor-supply weights from the ACS, we first impose a few sample restrictions. Respondents must be between 16 and 67 years old, be employed, and report a valid Standard Occupation Classification (SOC) code.³ The labor-supply weights equal the

² The linkage between the ACS and O*NET data is complicated by the occupation classification systems changing over time. In some cases, two occupations are combined to form a single occupation. In others, an occupation is split into two or more different occupations. The ACS uses the 2000 SOC classification for the 2004—2009 surveys, the 2010 SOC classification for the 2010—2017 surveys, and the 2018 SOC classification for 2018—2019. We use a crosswalk to harmonize the SOC codes across the survey years, and then use the 2018 SOC codes to link to the O*NET data. We will provide data sets, crosswalks, annotated STATA code, and other supporting documentation upon request.

³ Limiting the sample to those who report a SOC code is a necessary restriction, as it provides the means through which the ACS and O*NET data are linked.

number of hours usually worked and weeks worked during the previous year, which follows both Autor, Levy, and Murnane (2003) and Deming (2017).⁴ The full ACS-O*NET matched sample, which spans 2004—2019, consists of 13,233,391 observations.

After linking the O*NET and ACS data sets, the resulting longitudinal data set has 449 (out of a possible 471) unique occupations observed over the sample period (2004—2019). In Table 2.2, we provide the sample means and standard deviations, and estimates for the standard deviations within and between occupations for the task-intensity measures. In columns one and two, we report the labor-supply weighted sample means and standard deviations. On average, respondents work in occupations with task intensities for cognitive—whether nonroutine or routine—and social skills in similar ranges (4.7—5.4), but they report much lower intensities when it comes to physical work (routine manual and nonroutine manual physical) (3.1—3.4). In columns three and four, we report the within and between occupation standard deviations. These calculations require the aggregation of the individual-level data to the occupation-year level, thereby creating a panel of occupations. The smaller estimates in column three (relative to column four) suggest less variation in the

Table 2.2 – Summary Statistics for the Task Intensity Measure

Task	Mean	Standard Deviation	Within Occupation Standard Deviation	Between Occupation Standard Deviation	Ratio of Between and Within Standard Deviations
	(1)	(2)	(3)	(4)	(5)
Nonroutine Cognitive Analytical	4.72	1.66	0.49	1.61	3.29
Nonroutine Cognitive Interpersonal	5.41	1.60	0.58	1.52	2.62
Routine Cognitive	5.10	1.06	0.43	1.14	2.65
Routine Manual	3.42	1.47	0.44	1.83	4.16
Nonroutine Manual Physical	3.05	1.56	0.30	1.67	5.57

⁴ Because the measure for weeks worked in the ACS is a factor variable in lieu of a continuous measure, we use the mid-point in the ranges for each of the measure’s values (1—6). The vast majority workers report working between 50 and 52 weeks per year. As such, the weight for these workers would equal hours usually worked times 51 (the midpoint).

Social Skill	4.94	1.58	0.79	1.53	1.94
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Notes: Columns 1 and 2 of the table presents summary statistics for the full ACS-O*NET sample, which spans 2004-2019. In total, the sample consists of 13,233,391 respondents for these two columns of estimates, and the statistics are computed using the labor-supply weights described in Section 2.2.1. Columns 3 and 4 provide estimates for the *within* and *between* variation in the task intensities, which requires aggregating the individual-level data to the occupation-year level. The aggregation ultimately results in a longitudinal data set. The `xtsum` command from STATA was used to compute these estimated standard deviations. Column 5 provides the ratio of the between standard deviation to the within standard deviation (i.e. divides column 4 by column 3). Sample weights are not permitted in the calculation of the within and between occupation standard deviations; however, the labor-supply weights were used in the aggregation of the data to the occupation-year level.

task intensities within occupation than across occupations. However, the extent to which the variation within occupations is less than that between occupations varies by task. For example, the standard deviation between occupations is approximately two times larger than it is within occupations for social skill tasks. However, the between estimate is over five times larger than the within estimate for nonroutine manual physical tasks.

Task-age profiles.

We use the ACS-O*NET linked data (described above) to construct age profiles for the task intensity measures. Ultimately, the goal of these plots is to examine how the task content of work changes over people’s working lives. We construct these profiles for several different types of workers, which vary by demographic (i.e., gender, race/ethnicity) and educational characteristics.⁵ The process to produce the task-age profiles involves two steps. The first step is to aggregate the data to the appropriate level. Our analysis to generate the plots involves fitting locally weighted scatterplot smoothing of the task intensity measure against age. For example, when we construct the task-age profiles by race and ethnicity, we aggregate to race/ethnicity-age cells. As another example, when we examine race/ethnicity-gender differences, we aggregate the data to the race/ethnicity-gender-age level. The second step is to group the task intensity variables into centiles (100 bins), which creates a 0—100

⁵ For our findings with respect to race/ethnicity, we are unable to follow the Office of Management and Budget (OMB) standards, as the sample sizes for the American Indian and Alaska Native (AIAN) and Native Hawaiian or Other Pacific Islanders (NHOPI) groupings are small and, therefore, potentially unreliable.

scale (measured on the y -axis). The third and final step is to fit a LOWESS regression model with the task-intensity centile as the dependent variable and age as the explanatory variable.

2.2.3. Supplementary analysis using the Occupation Requirements Survey (ORS) and the ACS.

Tradeoffs exist between the O*NET and ORS⁶ occupation-level data sets. The O*NET has administered surveys since 1998 and the ORS began in 2018. Thus, it is not possible to study trends in the task content of work with the ORS, but it is with O*NET. An ordinal scale is used in the O*NET survey (0—7), but economically meaningful margins are provided by the ORS (e.g., hours spent standing, pounds lifted, hours spent sitting, etc.). We supplement the analysis from Section 2.2.1 by merging the 2018 Occupational Requirements Survey (ORS) with the 2018 ACS sample.⁷ We use age and demographic information from the ACS to construct age profiles for a select set of occupational requirements across demographic and education groups.

The 2018 ORS dataset provides job-related information on three general categories of occupational requirements—education, training, and experience; environmental conditions; and physical demands. In total, there are 285 separate requirements that report a non-missing value for at least one occupation, which vary in nature and span different moments of the survey distribution.⁸ After converting the O*NET-SOC codes to the 6-digit level, the total number of unique occupations in our analysis totals 305.⁹

⁶ ORS data are available from the Bureau of Labor Statistics. The raw dataset is presented in long-form in terms of occupation and occupational requirements. We reshaped it into wide-form, such that the unit of observation is a six-digit occupation, prior to merging it with the 2018 ACS sample.

⁷ Data are merged at the 6-digit occupational code level using the 2010 O*NET-SOC 2010. Prior to the merge, the 2010 O*NET-SOC codes were crosswalked to the 2018 taxonomy, consistent with the SOC codes in the 2018 ACS sample. Of the 311 occupations listed in the ORS (with values for any of the task values), we successfully matched 250 of them at the 6-digit SOC level. However, some ACS occupational codes are reported using wildcard characters in the fourth, fifth, or sixth digit. For these cases, data are merged at the 3, 4, or 5-digit level, respectively. The total number of unique occupations in the final data set is 305.

⁸ Moments include the mean and the 10th, 25th, 50th, 75th, and 90th percentile. We use the mean exclusively in our analysis.

⁹ The number of occupations for which the ORS dataset reports a non-missing value varies across requirements. For instance, the most prevalent requirement across all occupations is the “Percent of Day Where Standing is Required.” This requirement is reported for 218 out of the 305 occupations. On the other hand, the requirement “Percent of Workers in Proximity to Moving Mechanical Parts” is only reported for one occupation. The coverage for the rest of the 285 requirements falls somewhere in between these extremes. Because better

In our analysis, we use six occupational requirements that proxy for physical tasks.¹⁰ Namely, these are the maximum amount of weight in pounds that must be lifted or carried, the number of hours spent standing each day, the number of hours sitting each day, the percent of workers in the occupation with the option to sit or stand, stooping, and gross manipulation with both hands. The task-age profile plots created using the ACS-ORS are created analogously to those described in Section 2.2.1. In particular, the individual-level ACS-ORS data are aggregated to the age-demographic/education level, the task intensity variables are split into centiles, and then a locally weighted regression (LOWESS) is used to display the relationship between the particular task and age.

2.2.4. NLSY79-O*NET.

The NLSY79 is a nationally representative survey of individuals between the ages of 14 and 21 living in the United States in 1979. The birthdays of the 1979 cohort range from January 1, 1957 to December 31, 1964. The NLSY79 has been conducted biennially since 1994 and, as of the last round conducted in 2018, 6,878 of the initial 12,686 respondents remain in the sample. After eliminating observations for people who did not report a 3-digit occupational code, we are able to match 7,083 respondents, as of the last survey, to the O*NET panel data for the even years between 2004 and 2018.¹¹ Our NLSY79-O*NET sample includes 93 of the 98 possible minor group occupations listed by the Bureau of Labor Statistics.

coverage provides more variation in requirement intensity and a more complete and representative group of occupations and workers, we only consider requirements that are reported for at least a quarter of the 305 occupations, which is about 75 occupations.

¹⁰ Unfortunately, few, if any, clear measures of cognitive task intensity are available in the 2018 ORS. As such, the potentially-cognitive tasks available in the 2018 ORS are unlikely to be comparable to those from the O*NET-ACS analysis. The ACS is scheduled to release the 2020 data in Fall 2021. When those data are released, it will be possible to examine the 2020 ORS, which has more information on cognitive tasks.

¹¹ It is not possible to merge the NLSY79 and O*NET (also augmented by the labor-supply weights from the ACS) data sources at the detailed occupation level (i.e., 6-digit). To compute the task intensity measures for this part of our analysis, we aggregate the task intensity measures, while using the labor supply weights, to the minor group level (i.e., 3-digit). The aggregation to the minor group level provides a way to combine the two data sets. We eliminate respondents who report one of the missing minor group occupations, as we are unable to adjust the task intensity measures using the labor supply weights from the ACS due to the absence of these minor group occupation codes in the data set.

Table 2.3 – Summary Statistics

	All		50 and Older		Younger than 50	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Wage	10.61	1.03	10.64	1.04	10.59	1.02
Weekly Hours Worked	43.02	12.96	42.83	13.12	43.20	12.81
Multiple Jobs	0.09	0.29	0.09	0.29	0.09	0.29
Switched Occupation	0.25	0.43	0.28	0.45	0.23	0.42
Switched to Occupation Outside Firm	0.15	0.36	0.16	0.36	0.14	0.35
Switched to Occupation Within Firm	0.10	0.31	0.12	0.33	0.09	0.28
Weeks out of Labor Force	1.84	7.37	1.81	7.47	1.88	7.28
NR Cognitive Analytical	4.52	1.32	4.52	1.31	4.53	1.33
NR Cognitive Interpersonal	5.22	1.39	5.26	1.42	5.19	1.36
R Cognitive	5.07	0.87	5.06	0.87	5.09	0.87
R Manual	3.70	1.43	3.64	1.44	3.74	1.42
NR Manual Physical	3.32	1.50	3.26	1.49	3.37	1.50
Social Skill	4.87	1.46	4.49	1.53	5.25	1.29
Female	0.47	0.50	0.48	0.50	0.46	0.50
Hispanic	0.19	0.39	0.19	0.39	0.19	0.39
Black	0.28	0.45	0.28	0.45	0.29	0.45
Excellent – Childhood Health	0.55	0.50	0.56	0.50	0.55	0.50
Very Good – Childhood Health	0.28	0.45	0.28	0.45	0.28	0.45
Good – Childhood Health	0.13	0.34	0.13	0.34	0.14	0.34
Fair – Childhood Health	0.03	0.17	0.03	0.16	0.03	0.17
Poor – Childhood Health	0.01	0.08	0.01	0.08	0.01	0.09
Marriage Status: Never Married	0.14	0.34	0.12	0.33	0.15	0.36
Marriage Status: Married	0.59	0.49	0.59	0.49	0.59	0.49
Marriage Status: Separated	0.04	0.21	0.04	0.20	0.05	0.21
Marriage Status: Divorced	0.21	0.40	0.22	0.41	0.19	0.39
Marriage Status: Widowed	0.02	0.14	0.03	0.16	0.01	0.11
North East Region	0.15	0.36	0.15	0.36	0.15	0.36
North Central Region	0.25	0.43	0.24	0.43	0.25	0.43
South Region	0.41	0.49	0.40	0.49	0.41	0.49
West Region	0.20	0.40	0.20	0.40	0.19	0.39
High School Graduate	0.43	0.49	0.41	0.49	0.45	0.50
Some College	0.26	0.44	0.26	0.44	0.26	0.44
College Graduate	0.24	0.43	0.27	0.44	0.22	0.41
Age	49.64	5.25	54.18	2.94	45.23	2.56
Rotter Score (1979)	8.70	2.40	8.59	2.41	8.81	2.38
Rotter Score (2014 and Later)	7.29	2.27	7.24	2.24	7.35	2.30
AFQT (1981)	44.49	28.68	45.09	28.62	43.91	28.72
Observations	36,322	36,322	17,913	17,913	18,409	18,409

With the NLSY79, we can relate an individual's work history to occupational task intensity from mid- to late-career. We examine the relationship between task intensity and wages,¹² hours worked, weeks out of the labor force,¹³ occupational sorting (within and between firms), and holding multiple jobs. Table 2.3 shows the summary statistics for the outcome variables as well as demographic, health, and cognitive/non-cognitive characteristics for the full sample and then also for subsamples of respondents 50 and older and younger than 50.

3. Trends in and Age Profiles of the Task Content of Work in the United States

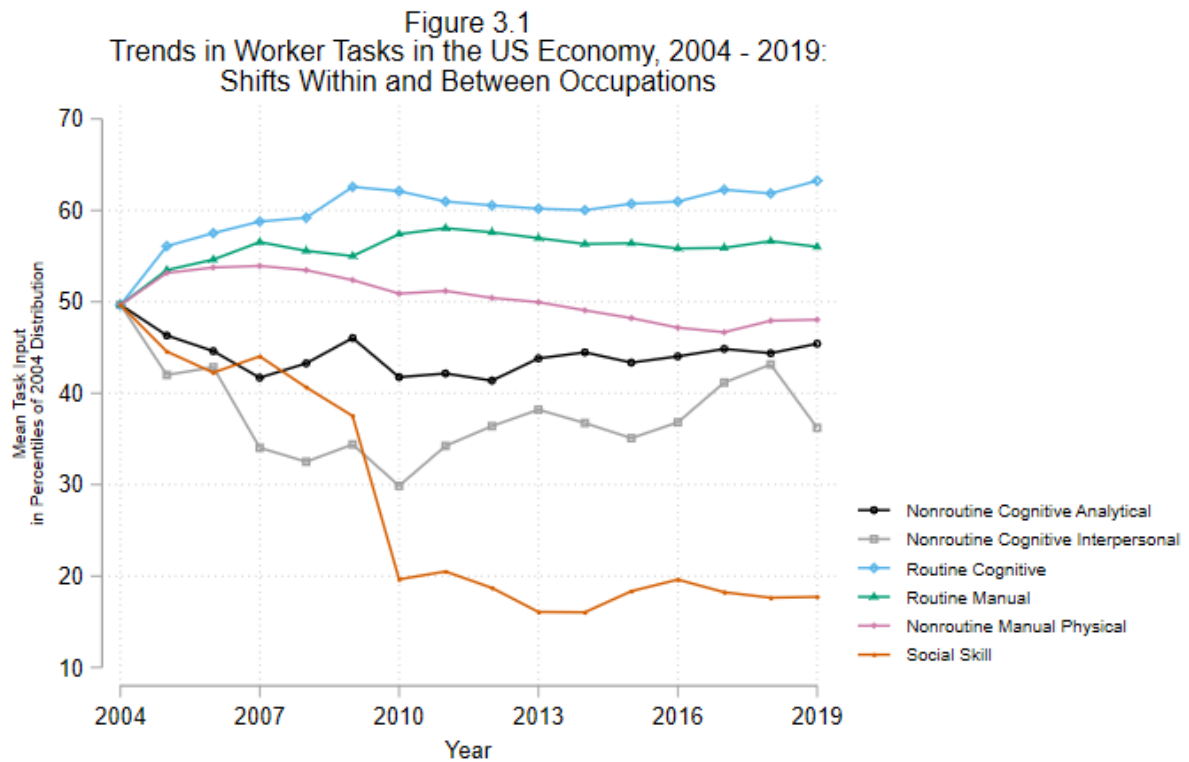
3.1. National and Age-Specific Trends for the US Economy

In Figure 3.1, we show the aggregate labor market trends in worker tasks in the US economy over the 2004—2019 period. The figure is constructed by linking task measures created via the longitudinal data from O*NET and employment data from the American Community Surveys (ACSs). Once combined, the individual-level data are aggregated to 6,466 gender-education-industry-year cells. We then compute the mean task intensity for each centile for each task in 2004 as well as the mean task intensity for each task in each year and record the centile to which the mean value in each subsequent year (e.g., 2005, 2006, and so on) corresponds in the 2004 task distribution. By construction, the task measures equal 50 in 2004. The construction of the figure follows Autor, Levy, and Murnane (2003) as well as Deming (2017), but our task intensity measures, like those in Atalay et al. (2020) and Ross (2016, 2017), have two components: workers moving to different occupations and changes in task intensity within occupations. Figure 3.1 follows the approach used by Atalay et al.

¹² Our regressions of wage rates on the task intensity measures use the log-level specification in lieu of the poisson functional form. However, the results are almost identical when using poisson regression.

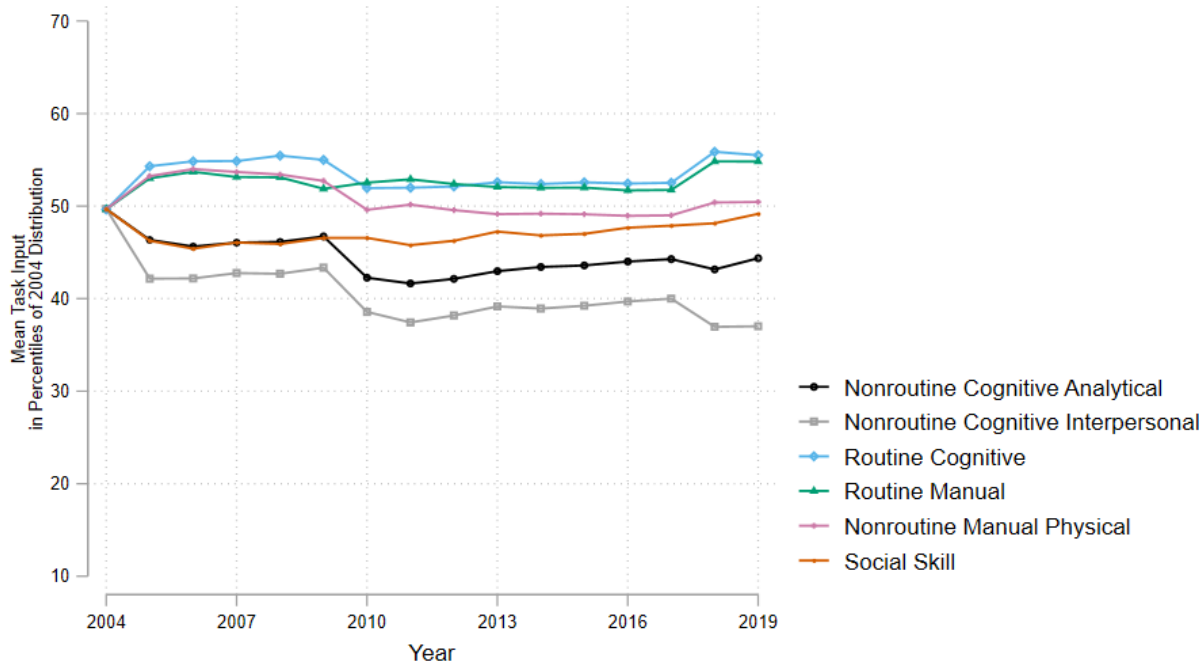
¹³ The NLSY-79 collects information on how many weeks an individual was out of the labor force since their last interview. Because the NLSY-79 conducts interviews biennially, the number of weeks out of the labor force is computed over two years. Because some individuals completely exit the labor force and do so over multiple periods, we cannot examine how the previous period's task intensities impact the number of weeks out of the labor force, as the respondent may not have had a job in the most recent period. Therefore, we use values from 2004 for the task intensity measures to examine the relationship between the tasks and time out of the labor force.

(2020) in that the aggregate trends reflect both flows of workers across occupations and changes in tasks within occupations.



Notes: The figure is constructed by linking task measures created via panel of occupations from Occupation Information Network (O*NET) and employment data from the American Community Surveys (ACS) from 2004-2019. The ACS data is used to produce employment-weighted (hours*weeks worked) task intensity estimates. Once combined, the individual-level data are aggregated to 6,466 sex-education-industry-year cells. With the aggregated data, the mean task intensity for each centile is computed for each task in 2004. We then compute the mean task intensity for each task in each year and record the centile to which the mean value corresponds in the 2004 task distribution. By construction, the task measures equal 50 in 2004. The construction of the figure follows Autor, Levy, and Murnane (2003) as well as Deming (2017), but our task intensity measures, like those in Atalay et al. (2020) and Ross (2016, 2017), have two components: workers moving to different occupations and changes in task intensity within occupations.

Figure 3.2
Trends in Worker Tasks in the US Economy, 2004 - 2019:
Shifts Between Occupations



Notes: The figure is constructed by linking task measures created from the 2004 Occupation Information Network (O*NET) and employment data from the American Community Surveys (ACSs) from 2004-2019. The ACS data is used to produce employment-weighted (hours*weeks worked) task intensity estimates. Once combined, the individual-level data are aggregated to 6,466 sex-education-industry-year cells. With the aggregated data, the mean task intensity for each centile is computed for each task in 2004. We then compute the mean task intensity for each task in each year and record the centile to which the mean value corresponds in the 2004 task distribution. By construction, the task measures equal 50 in 2004. The construction of the figure closely follows Autor, Levy, and Murnane (2003) as well as Deming (2017).

Figure 3.2 follows the approaches used by Autor, Levy, and Murnane (2003), Autor and Price (2013), and Deming (2017), which excludes the within-occupation changes in task content and instead focuses on flows of workers across occupations over time. Whereas Atalay et al. (2020) report that Autor, Levy, and Murnane (2003) understate the extent of the changes in task content, our findings indicate that the variation within occupations exceeds that of changes in employment shares across occupations for particular tasks, such as routine cognitive and social skills task intensities. Between 2004 and 2019, routine cognitive task intensity rises by 13 centiles in Figure 3.1 but only rises by five centiles in Figure 3.2, and social skill task intensity falls by 32 centiles in Figure 3.1 and only falls by one centile in Figure 3.2. The starting and ending points for the other tasks are similar across the two figures.

In Figure 3.3, we investigate age-specific differences in task content over the sample period. The figure is created identically to Figure 3.1, except that the samples used to generate the timeplots vary based on the age group: (i) 16—25, (ii) 26—35, (iii) 36—45, (iv)

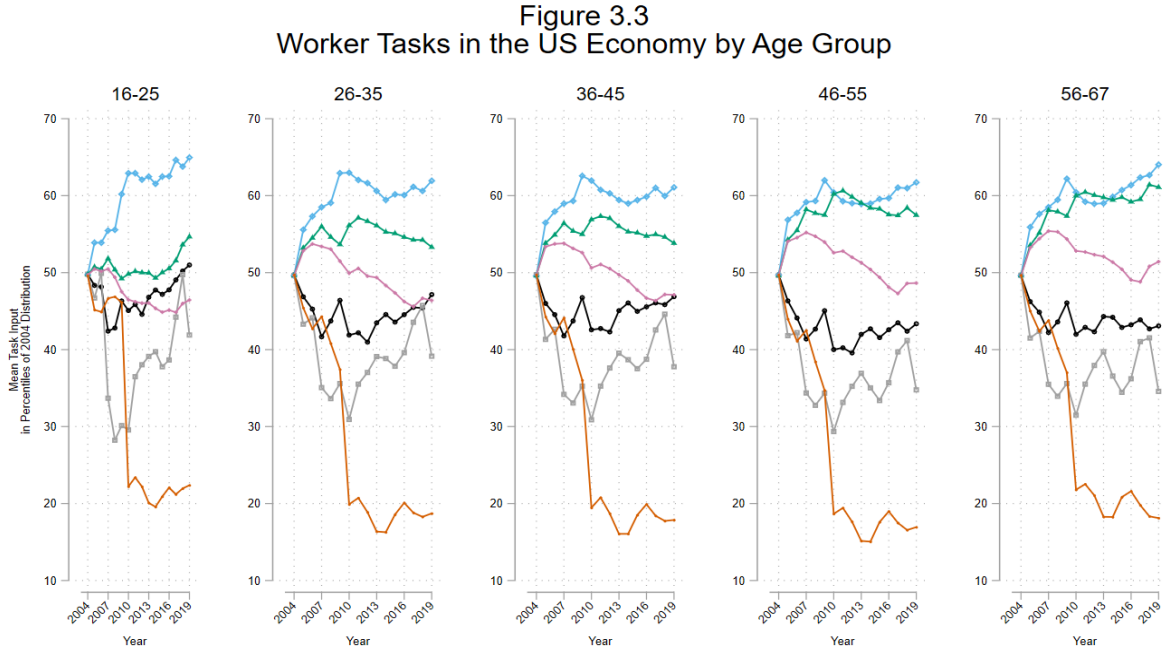
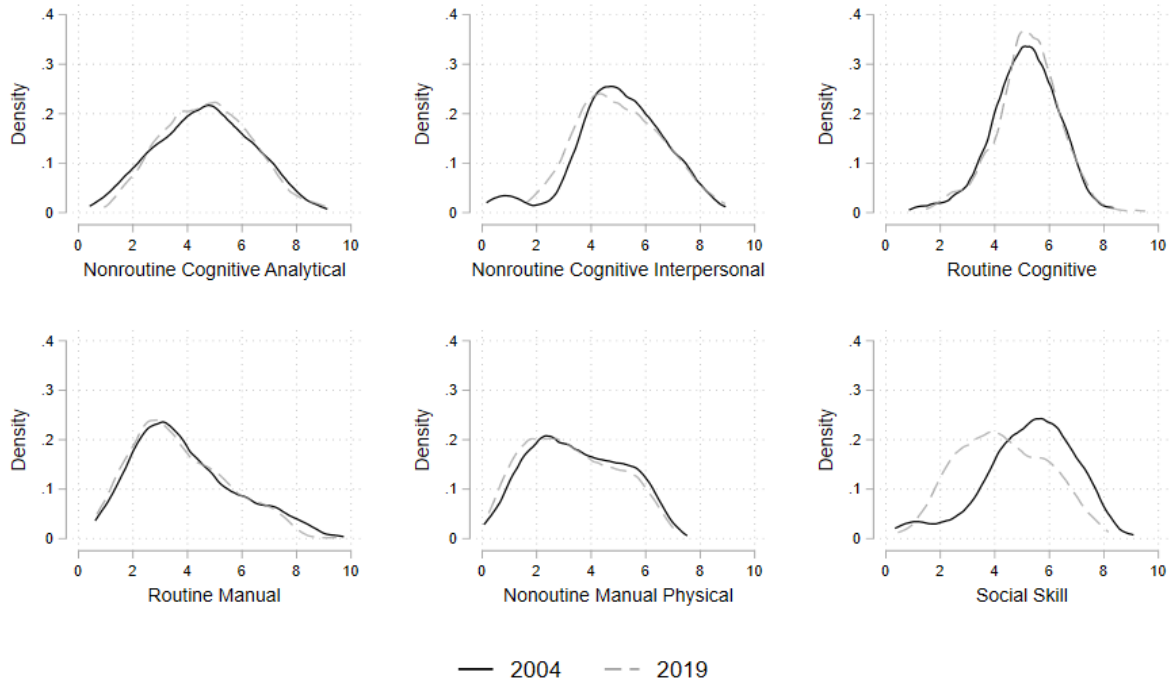


Figure 3.4
Density Plots for the Task Intensity Variables 2004 and 2019



Notes: The figure is constructed by linking task measures created via panel of occupations from Occupation Information Network (O*NET) and employment data from the American Community Surveys (ACSs) from 2004-2019. The ACS data is used to produce employment-weighted (hours*weeks worked) task intensity estimates. The individual-level data are aggregated to 5,278 occupation-year cells, and then a kernel smoother is applied to plot the distribution of the task intensity measures.

46—55, and (v) 56—67. Overall, comparisons of the task-intensity trends across the age groups suggest subtle differences in their respective trend lines. However, we observe the greatest rise in routine cognitive task intensity for the youngest and oldest workers, as the intensity rises by about 15 centiles for these two groups from 2004 to 2019. The rise for the other three age groups is around 10 centiles. Routine manual task intensity rises the most for the oldest workers, rising around 10 centiles from 2004 to 2019. It is also noteworthy that nonroutine manual physical task intensity rises slightly for the oldest workers, but it falls for workers under 55 over the same time horizon. Nonroutine cognitive tasks, both analytical and interpersonal, fall for all age groups, but these task intensities fall slightly more for the 46—55 and 56—67 age groups. Social skill task intensity plummets for all age groups, falling by about 30 centiles between 2004 and 2019.

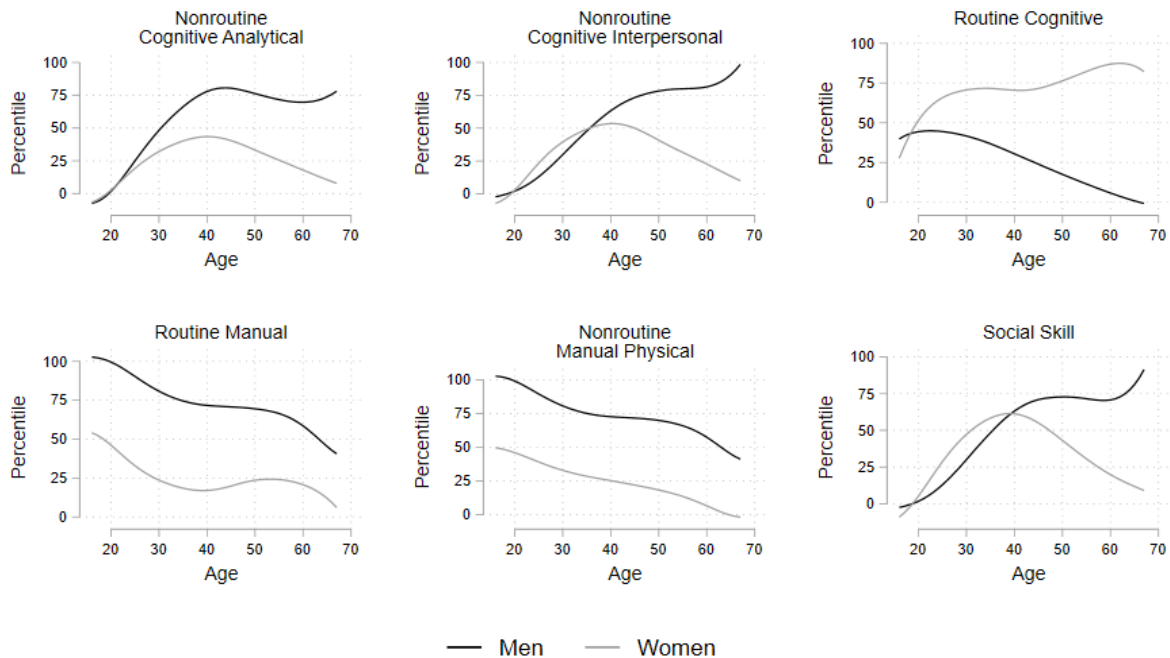
Figure 3.4 allows us to observe the shifts in the full distribution of the task intensity variables, which offers perspective regarding the magnitude of the changes in the task intensity measures from Figures 3.1, 3.2, and 3.3. The panels in Figure 3.4 plot the Kernel density estimate for each of the task variables. In an effort to see more clearly the patterns over the sample period, we plot only the first (2004) and last (2019) years of the sample. Although the shifts are subtle, the density plots illustrate leftward shifts in the distributions of the task variables, with the exception of routine cognitive task intensity. In fact, the shifts in the task intensity variable distribution suggest that the overall trends in Figures 3.1, 3.2, and 3.3 represent changes in mean task intensities rather than the influence of outliers.

3.2. Task-Age Profiles

Our analysis starts by plotting the task intensity variables, which are converted to centiles (100 bins), for men and women separately. From Figure 3.5, one observes that younger men and women are similar in terms of all task intensity variables, except those that require physical activity. Nonroutine cognitive, whether analytical or interpersonal, and social skill task intensity tends to rise over the working lives of men, but these intensities rise for

women until around mid-career before beginning to fall. Interestingly, the intensity at which women complete routine cognitive tasks rises with age, but the opposite is true for men. Workers, particularly men, tend to work in occupations with more extensive physical demands when younger, but tend to transition out of those jobs as they age.

Figure 3.5
Task Intensities and Aging
by Gender



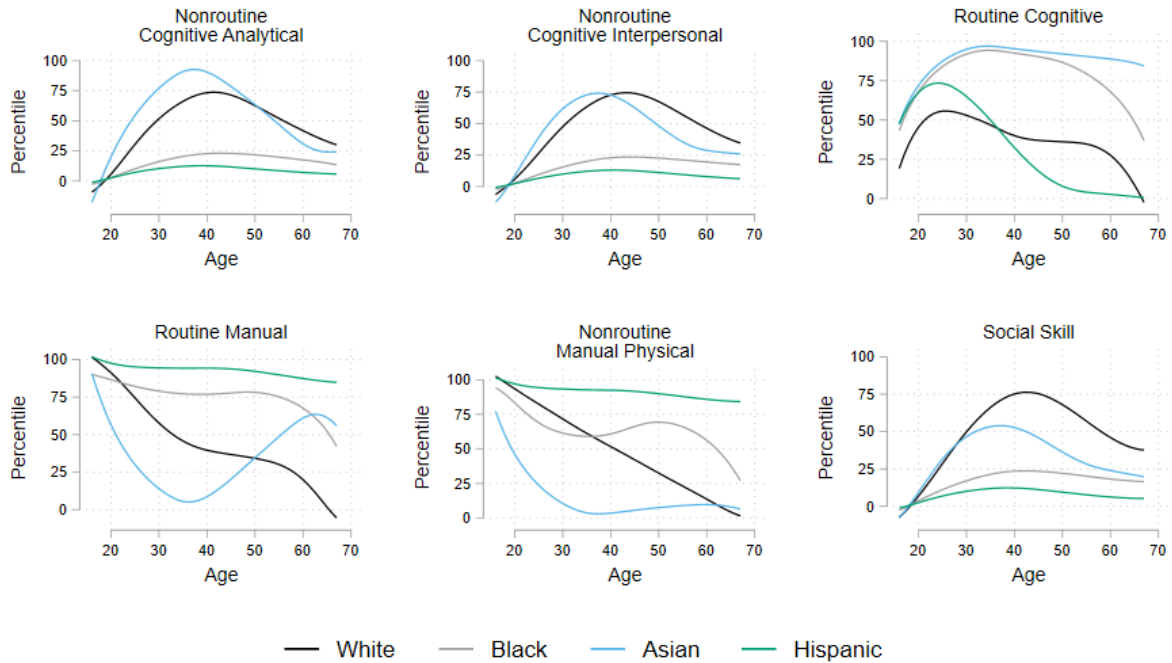
Notes: Using the combined O*NET and ACS data sets from 2004-2019 (described previously), the figure presents the relationship between the task intensity measures and age for men and women. To create the figure, we first aggregate the data to the 104 age-sex cells, and then separate the task intensity measures into centiles (100 bins). The plotted lines rely on a LOWESS fit with the bandwidth set at 0.8.

In Figure 3.6, we compute average task intensity measures by race/ethnicity and age. We focus on four racial/ethnic groups: White people, Black people, Hispanic people, and Asian people.¹⁴ From the panels in Figure 3.6, it is apparent that different racial/ethnic groups perform different types of tasks over their working lives. White and Asian workers experience significant upticks in the extent to which they perform nonroutine cognitive, both analytical and interpersonal, and social skill tasks in the occupation. By contrast, Black and

¹⁴ See the discussion in Section 2.2.1 regarding why AIAN and NHOPI respondents are excluded from our task-age profile analysis.

Hispanic workers tend to work in occupations that are low in nonroutine cognitive analytical, nonroutine cognitive interpersonal, and social skill task intensity. Conversely,

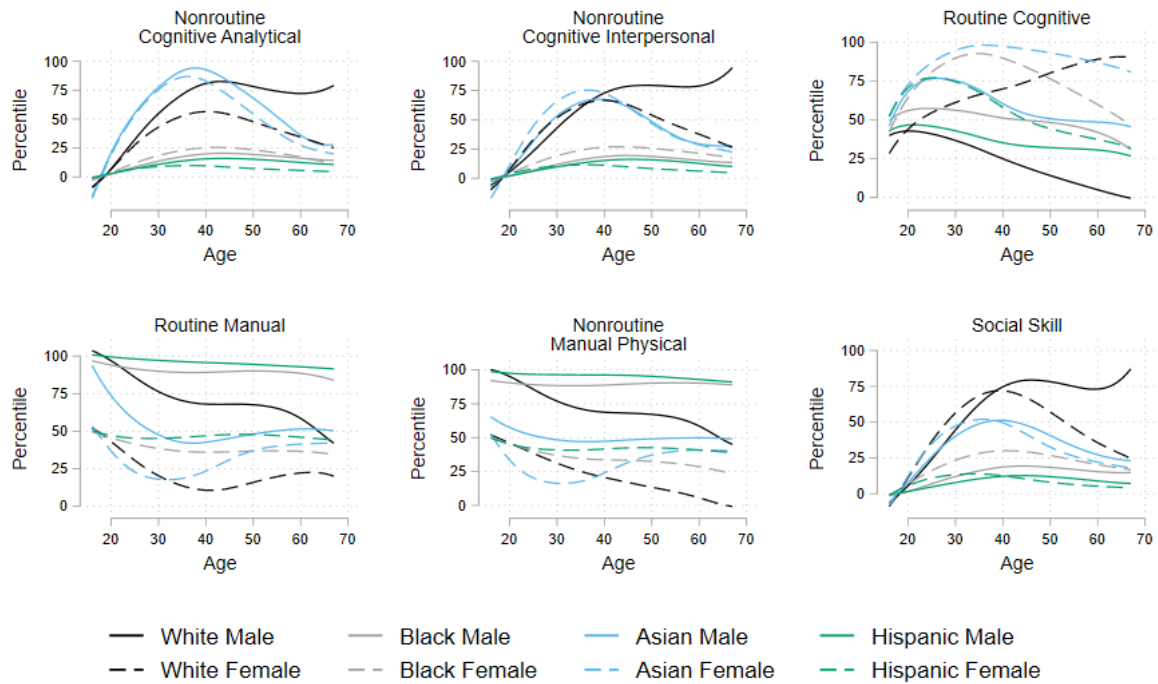
Figure 3.6
Task Intensities and Aging
by Race/Ethnicity



Notes: Using the combined O*NET and ACS data sets from 2004-2019 (described previously), the figure presents the relationship between the task intensity measures and age for different races/ethnicities. To create the figure, we first aggregate the data to the 364 age-race/ethnicity cells, and then separate the task intensity measures into centiles (100 bins). The plotted lines rely on a LOWESS fit with the bandwidth set at 0.8.

White and Asian workers tend to work in occupations that are low in physical task intensity, while Black and Hispanic workers tend to work in occupations that are high in physical task intensity. In fact, Hispanic workers are employed in occupations that are near the top of the physical task intensity distribution, and they tend to work in these types of occupations over their entire working lives. Physical task intensity tends to fall for Black workers, but the decline in physical task intensity as Black workers age is slower than it is for White and Asian people. Lastly, for routine cognitive task intensity, we observe all races/ethnicities tending to work in more cognitively routine occupations at young ages. This pattern continues until mid-career and then it reverses for Asian and Black workers, but it falls steadily with age for White and Hispanic workers.

Figure 3.7
Task Intensities for Different Genders and Races/Ethnicities by Age



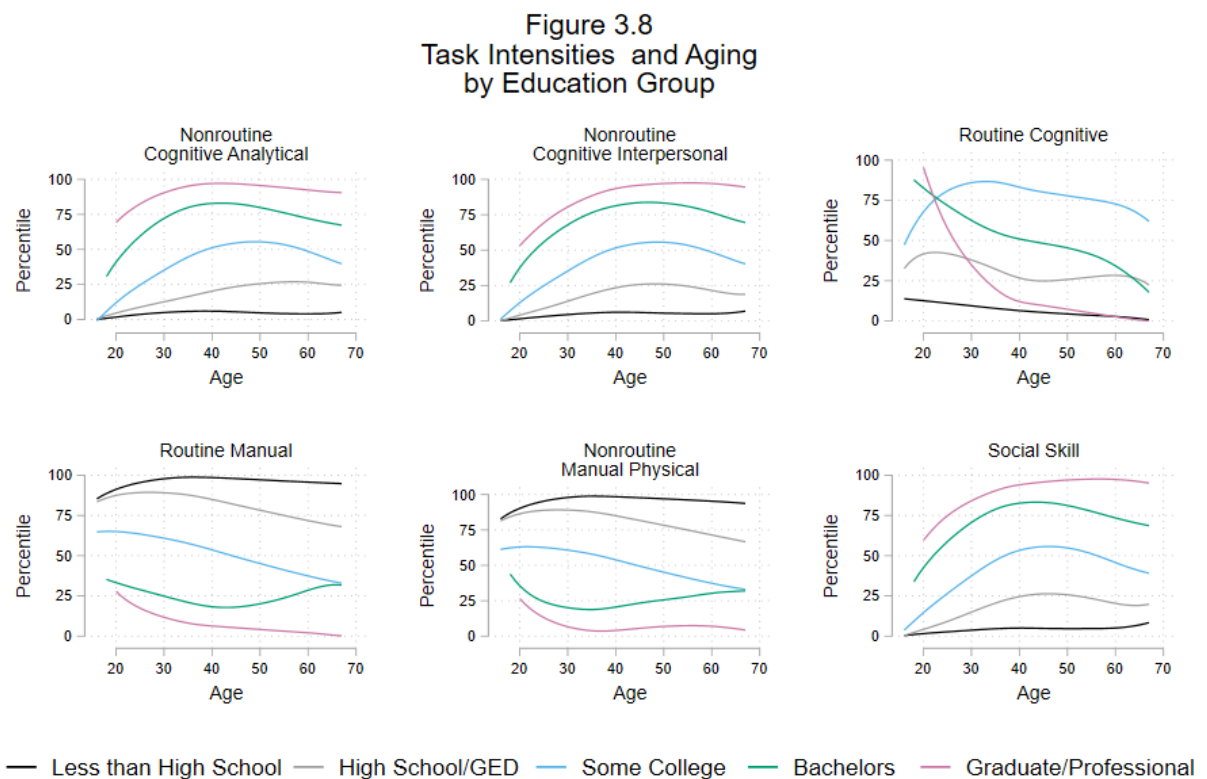
Notes: Using the combined O*NET and ACS data sets from 2004-2019 (described previously), the figure presents the relationship between the task intensity measures and age for different races/ethnicities. To create the figure, we first aggregate the data to the 520 age-race/ethnicity-gender cells, and then separate the task intensity measures into centiles (100 bins). The plotted lines rely on a LOWESS fit with the bandwidth set at 0.8.

In Figure 3.7, we present task-age profiles by race/ethnicity and gender. The solid lines represent men, while the dashed lines represent women. For nonroutine cognitive analytical, nonroutine cognitive interpersonal, and social skill task intensity, all race/ethnicity-gender groups except white men reveal a concave relationship. These intensities rise and either plateau or continue to rise until White men reach retirement age. The other race/ethnicity-gender groups experience rising intensity in these tasks, but that pattern tends to reverse around mid-career.

The intensity at which routine cognitive tasks are completed tends to rise in early career and then fall thereafter. The exception is White women, who increasingly work in occupations with high levels of routine cognitive task intensity as they age. In terms of

physical work, we observe, for the most part, a negative relationship between the intensity of physical tasks, either routine manual or nonroutine manual physical, and age. However, the rate at which the different racial/ethnic-gender groups transition out of physical work varies. White men and White women experience sharp drops in physical task intensity as they age. Alternatively, the rate at which the task intensity declines for Black and Hispanic people, both men and women, is much slower, particularly for Hispanic and Black men, as they tend to work in physically demanding occupations over their entire working lives.

In Figure 3.8, we examine the task intensities over the lifecycle for different education groups: less than high school, high school/GED, some college, Bachelor’s degree, and

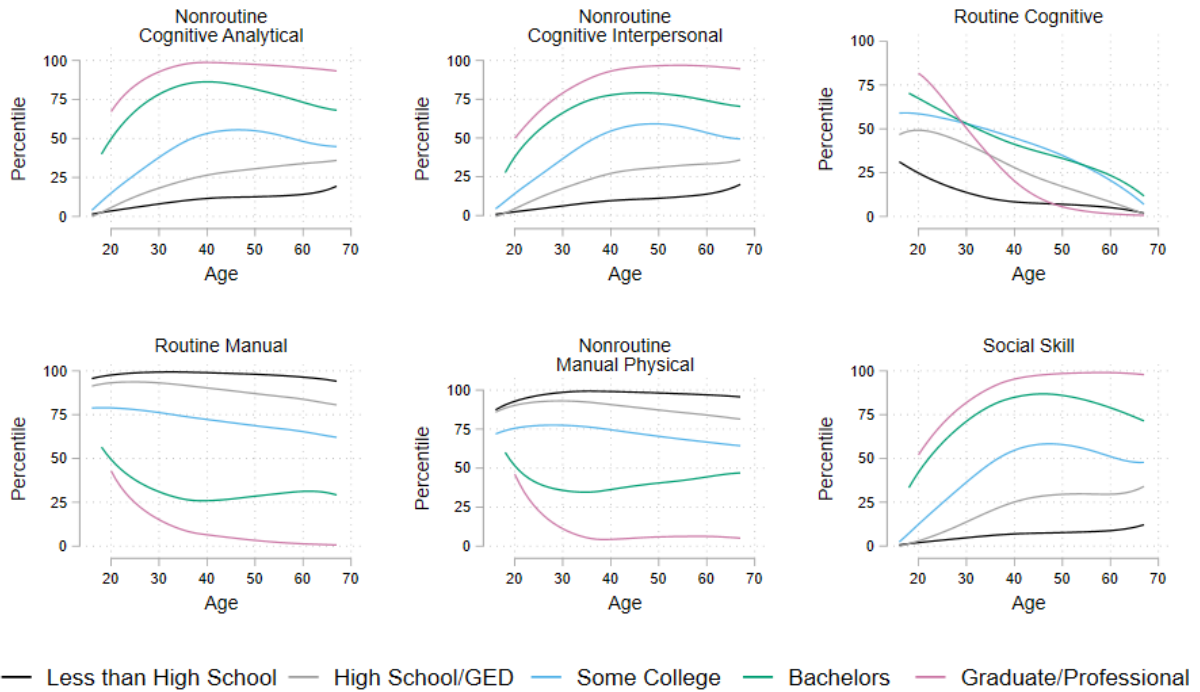


Notes: Using the combined O*NET and ACS data sets from 2004-2019 (described previously), the figure presents the relationship between the task intensity measures and age for different education groups. To create the figure, we first aggregate the data to the 254 age-education cells, and then separate the task intensity measures into centiles (100 bins). The plotted lines rely on a LOWESS fit with the bandwidth set at 0.8.

graduate/professional degree. The figure reveals expected patterns in which the workers

with higher education levels work in the most cognitively and least physically demanding occupations. This pattern holds by gender (Figures 3.9 and 3.10), race/ethnicity (Figures

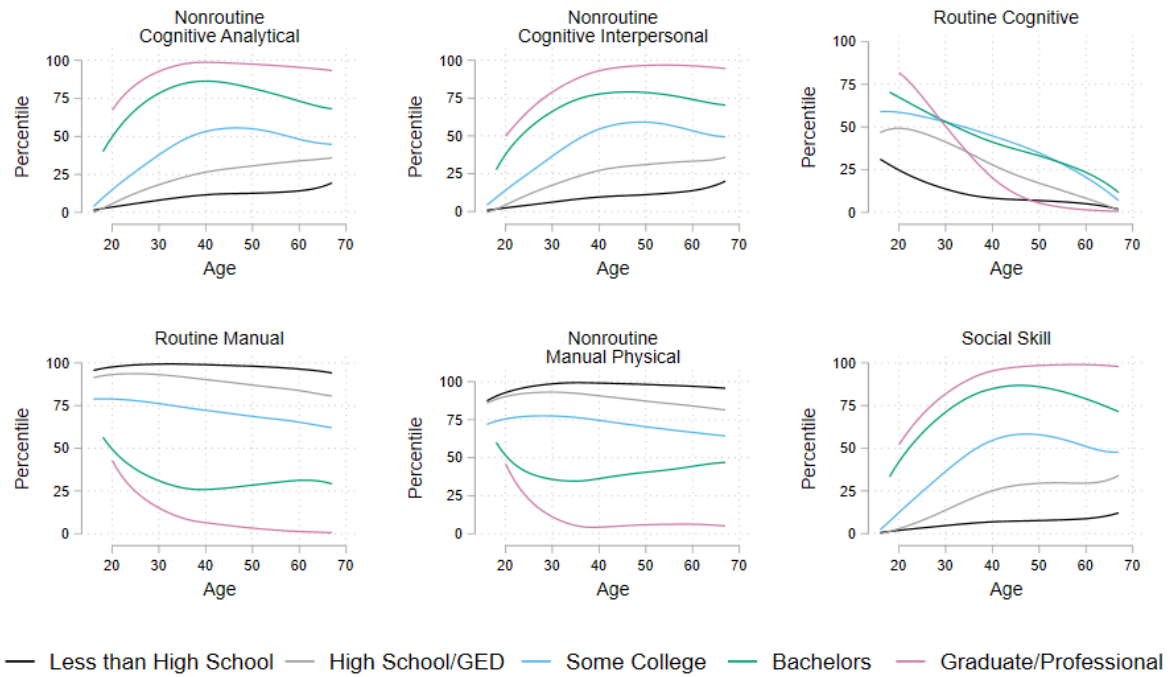
Figure 3.9
Task Intensities for Men in Different Education Groups by Age



Notes: Using the combined O*NET and ACS data sets from 2004-2019 (described previously), the figure presents the relationship between the task intensity measures and age for men in different education groups. To create the figure, we first aggregate the data to the 507 age-education-gender cells, and then separate the task intensity measures into centiles (100 bins). The plotted lines rely on a LOWESS fit with the bandwidth set at 0.8.

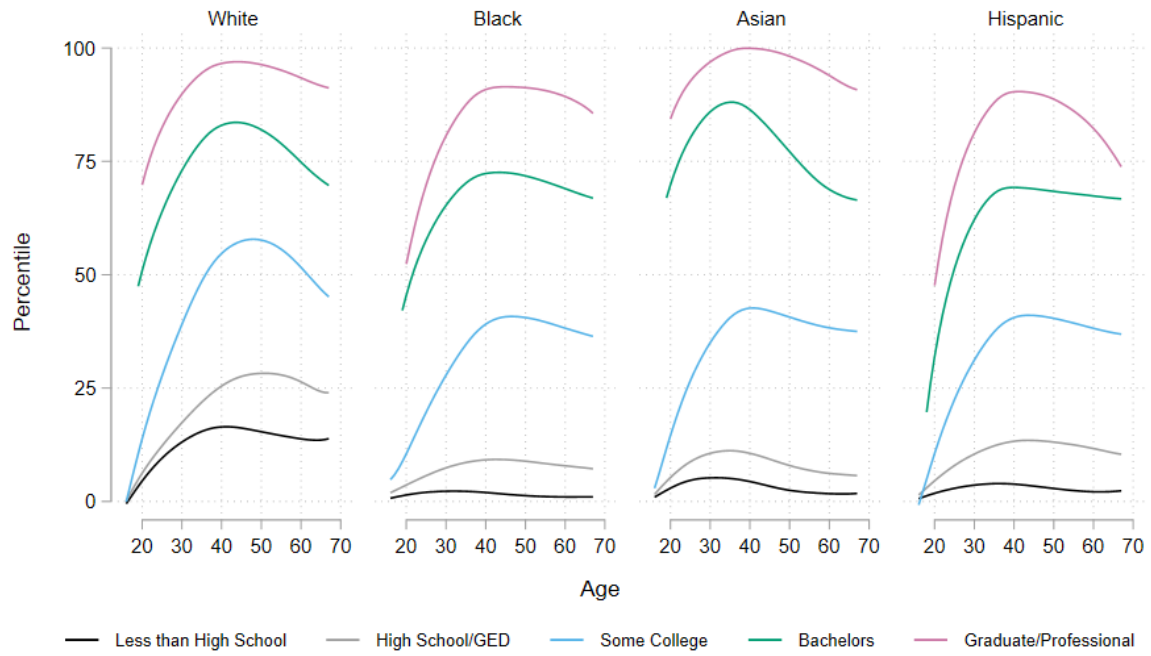
3.11—3.16), and race/ethnicity-gender (Figures 3.17—3.22). The overarching message from Figures 3.11—3.22 is that racial/ethnic-gender differences in task intensity are concentrated among workers with lower levels of education. For instance, in Figures 3.17, 3.18, and 3.22, we observe significant separation in these task intensities for White men versus all other groups at the lower education levels (Panel A). The same pattern holds for White women, but it is less pronounced (Panel B).

Figure 3.10
Task Intensities for Women in Different Education Groups by Age



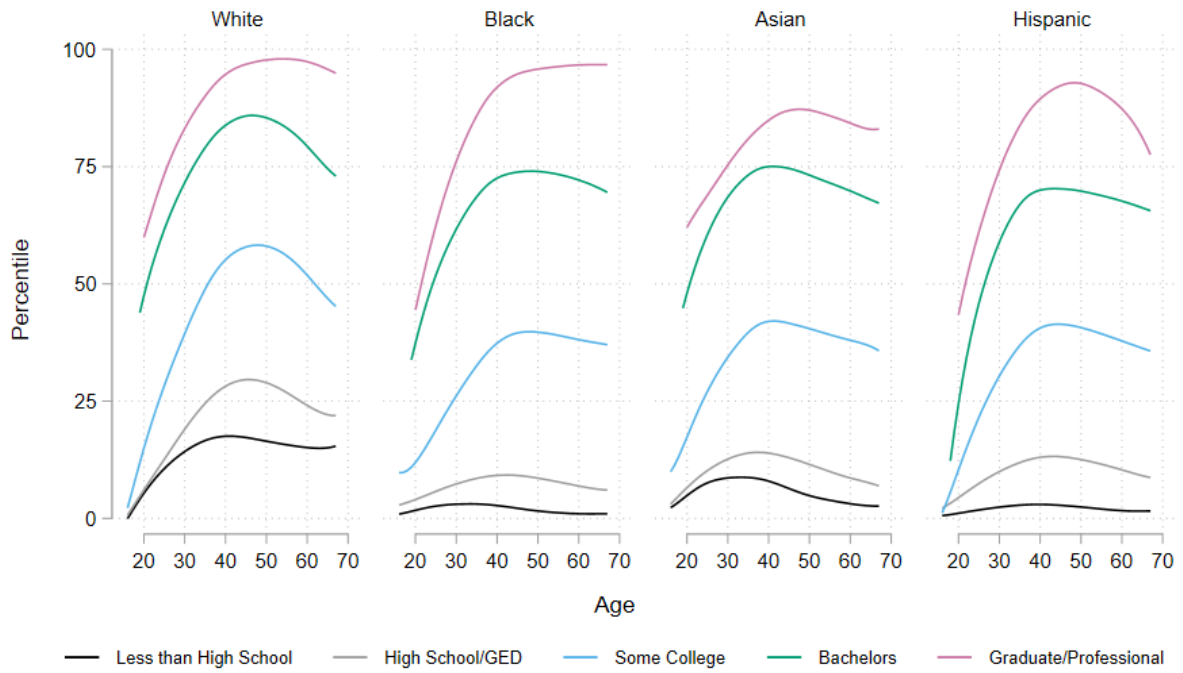
Notes: Using the combined O*NET and ACS data sets from 2004-2019 (described previously), the figure presents the relationship between the task intensity measures and age for women in different education groups. To create the figure, we first aggregate the data to the 507 age-education-gender cells, and then separate the task intensity measures into centiles (100 bins). The plotted lines rely on a LOWESS fit with the bandwidth set at 0.8.

Figure 3.11
 Nonroutine Cognitive Analytical Task Intensity and Aging
 by Race/Ethnicity and Education Group



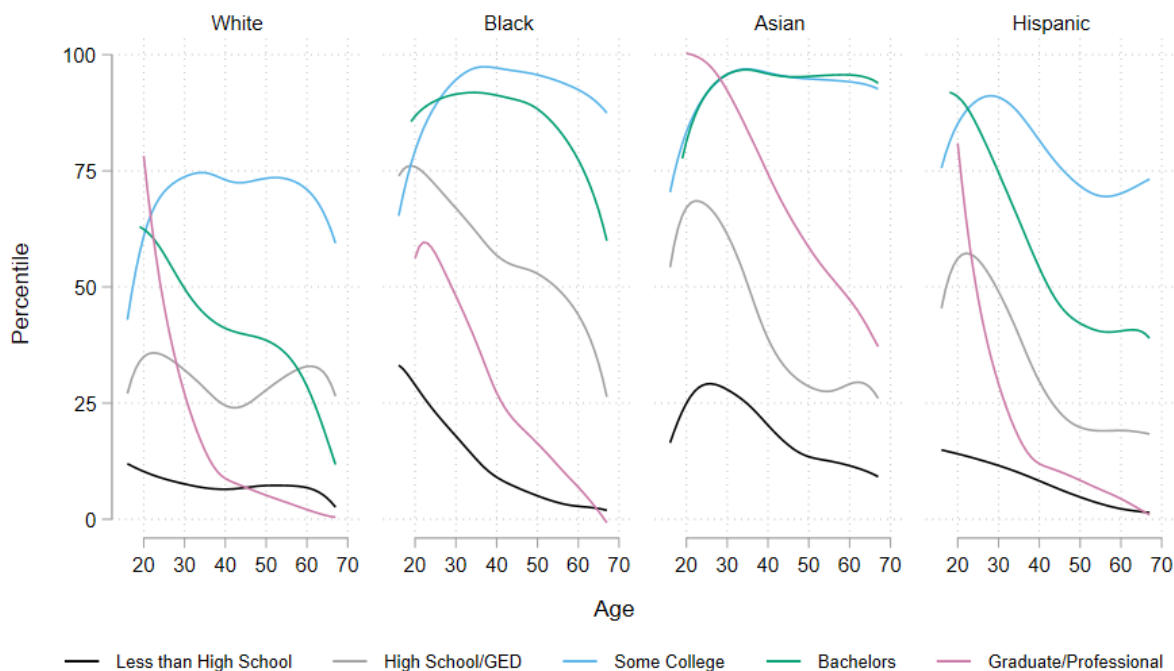
Notes: Using the combined O*NET and ACS data sets from 2004-2019 (described previously), the figure presents the relationship between nonroutine cognitive analytical task intensity and age for different race/ethnicity-education groups. To create the figure, we first aggregate the data to the 1013 age-education-race/ethnicity cells, and then separate the task intensity measures into centiles (100 bins). The plotted lines rely on a LOWESS fit with the bandwidth set at 0.8.

Figure 3.12
 Nonroutine Cognitive Interpersonal Task Intensity and Aging
 by Race/Ethnicity and Education Group



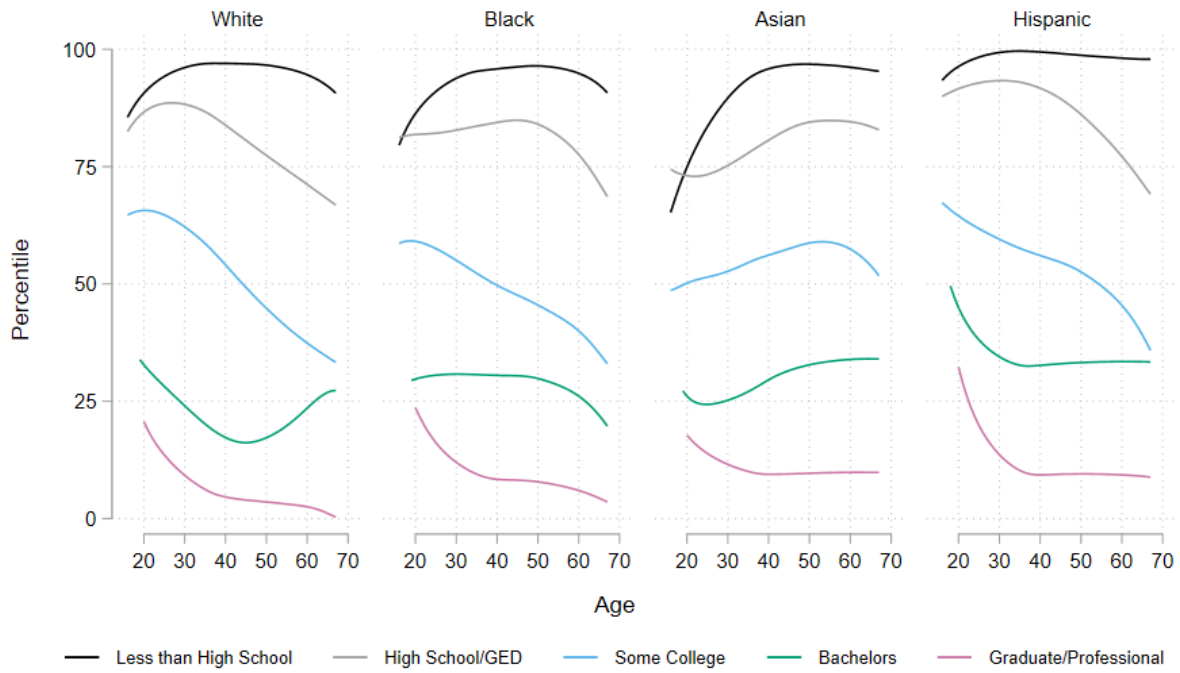
Notes: Using the combined O*NET and ACS data sets from 2004-2019 (described previously), the figure presents the relationship between nonroutine cognitive interpersonal task intensity and age different race/ethnicity-education groups. To create the figure, we first aggregate the data to the 1013 age-education-race/ethnicity cells, and then separate the task intensity measures into centiles (100 bins). The plotted lines rely on a LOWESS fit with the bandwidth set at 0.8.

Figure 3.13
 Routine Cognitive Task Intensity and Aging
 by Race/Ethnicity and Education Group



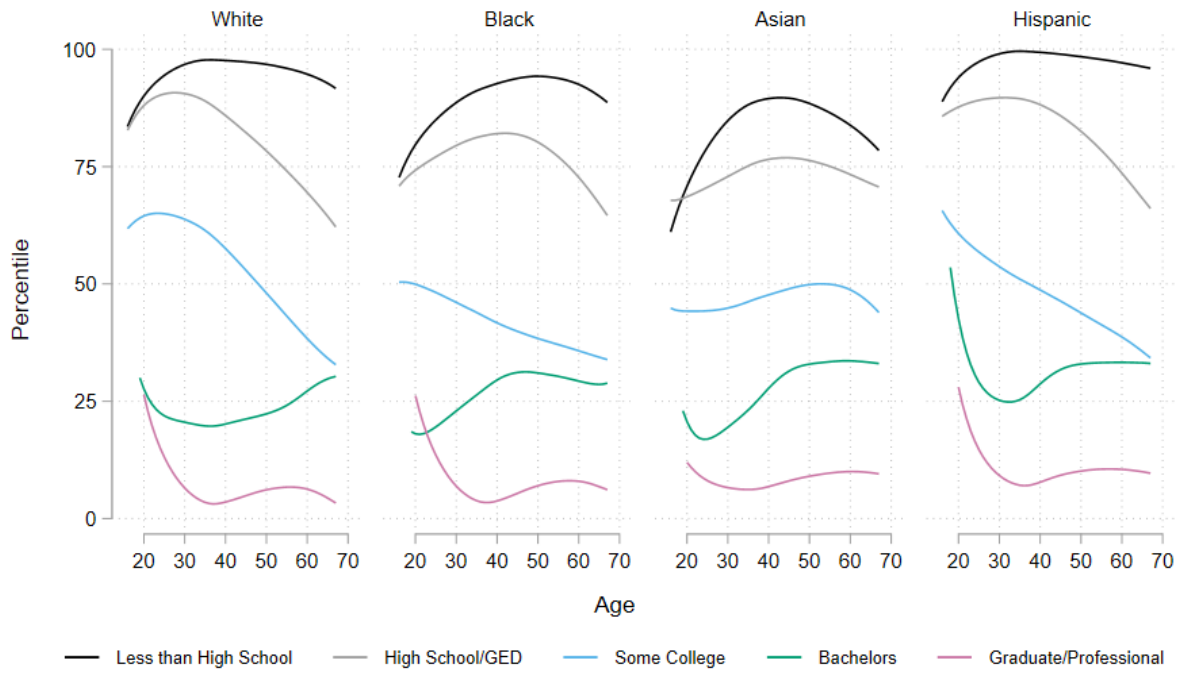
Notes: Using the combined O*NET and ACS data sets from 2004-2019 (described previously), the figure presents the relationship between routine cognitive task intensity and age for different race/ethnicity-education groups. To create the figure, we first aggregate the data to the 1013 age-education-race/ethnicity cells, and then separate the task intensity measures into centiles (100 bins). The plotted lines rely on a LOWESS fit with the bandwidth set at 0.8.

Figure 3.14
 Routine Manual Task Intensity and Aging
 by Race/Ethnicity and Education Group



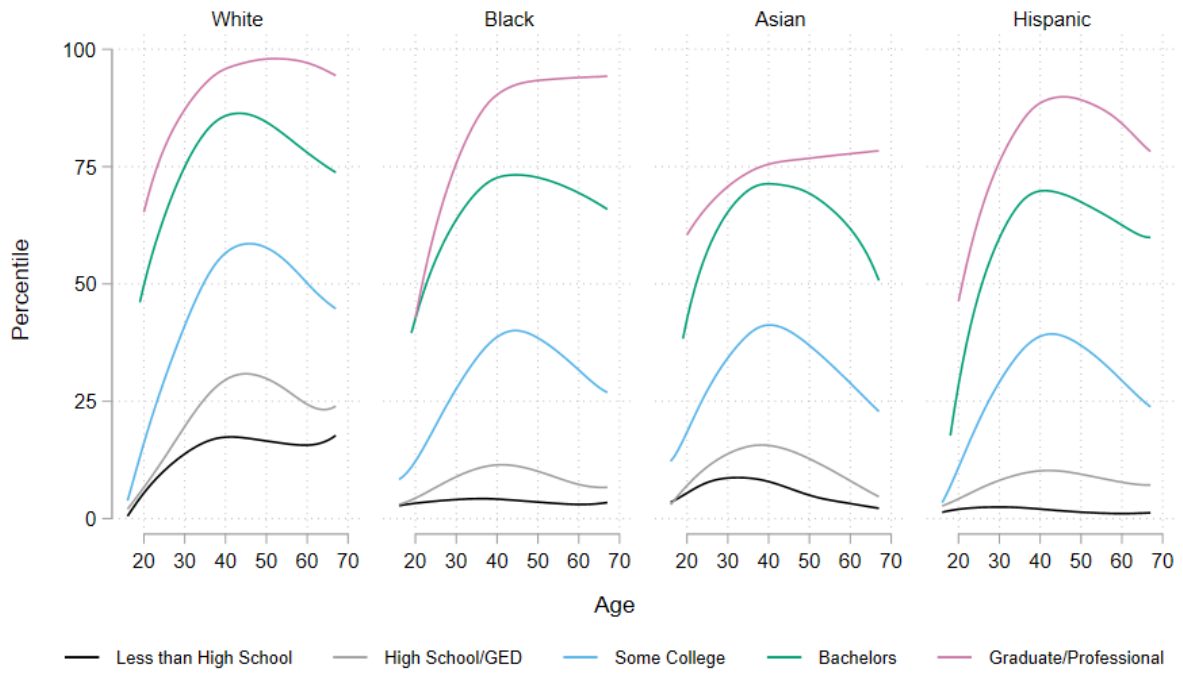
Notes: Using the combined O*NET and ACS data sets from 2004-2019 (described previously), the figure presents the relationship between routine manual task intensity and age for different race/ethnicity-education groups. To create the figure, we first aggregate the data to the 1013 age-education-race/ethnicity cells, and then separate the task intensity measures into centiles (100 bins). The plotted lines rely on a LOWESS fit with the bandwidth set at 0.8.

Figure 3.15
 Nonroutine Manual Physical Task Intensity and Aging
 by Race/Ethnicity and Education Group



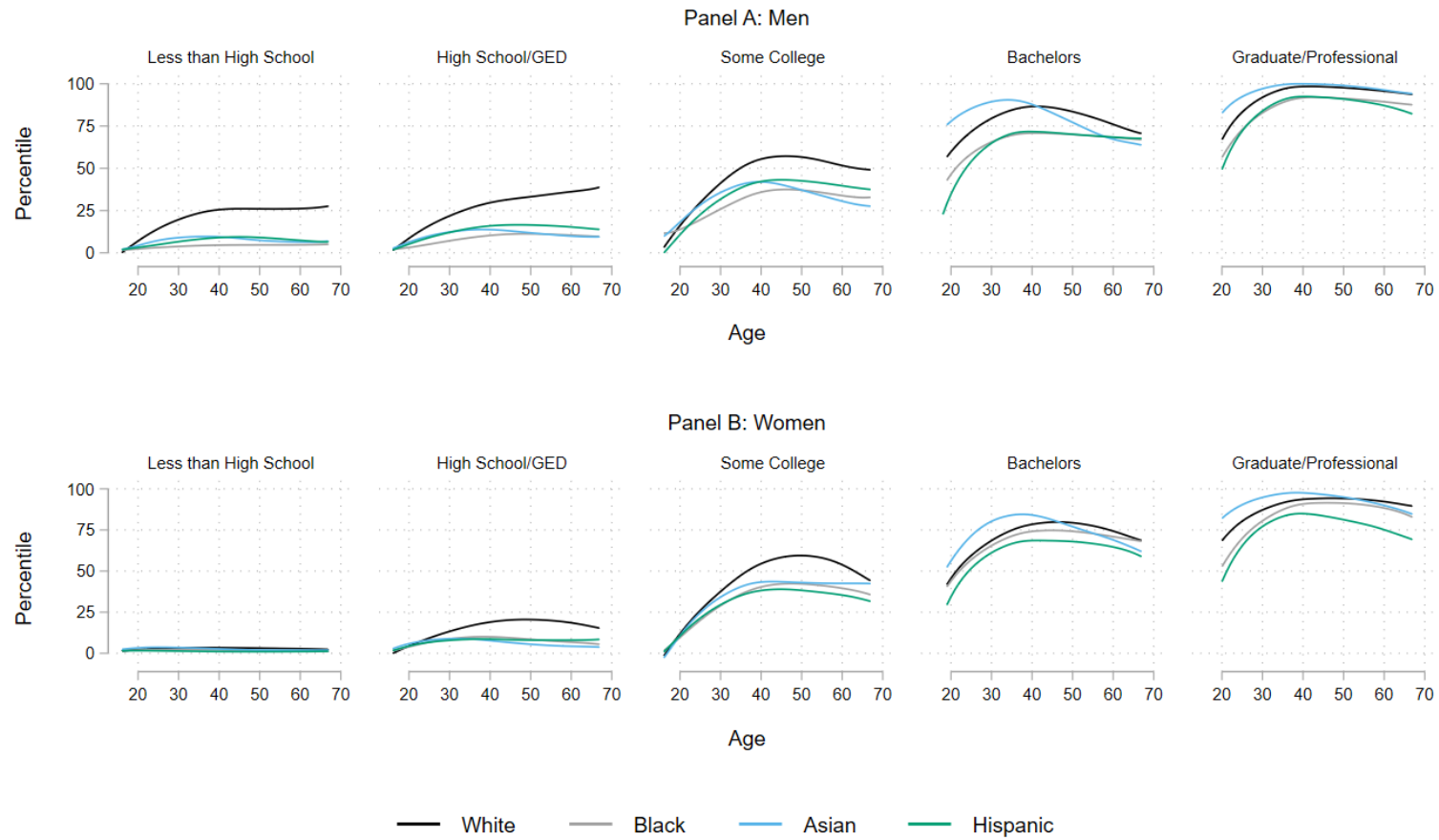
Notes: Using the combined O*NET and ACS data sets from 2004-2019 (described previously), the figure presents the relationship between nonroutine manual physical task intensity and age for different race/ethnicity-education groups. To create the figure, we first aggregate the data to the 1013 age-education-race/ethnicity cells, and then separate the task intensity measures into centiles (100 bins). The plotted lines rely on a LOWESS fit with the bandwidth set at 0.8.

Figure 3.16
Social Skill Task Intensity and Aging
by Race/Ethnicity and Education Group



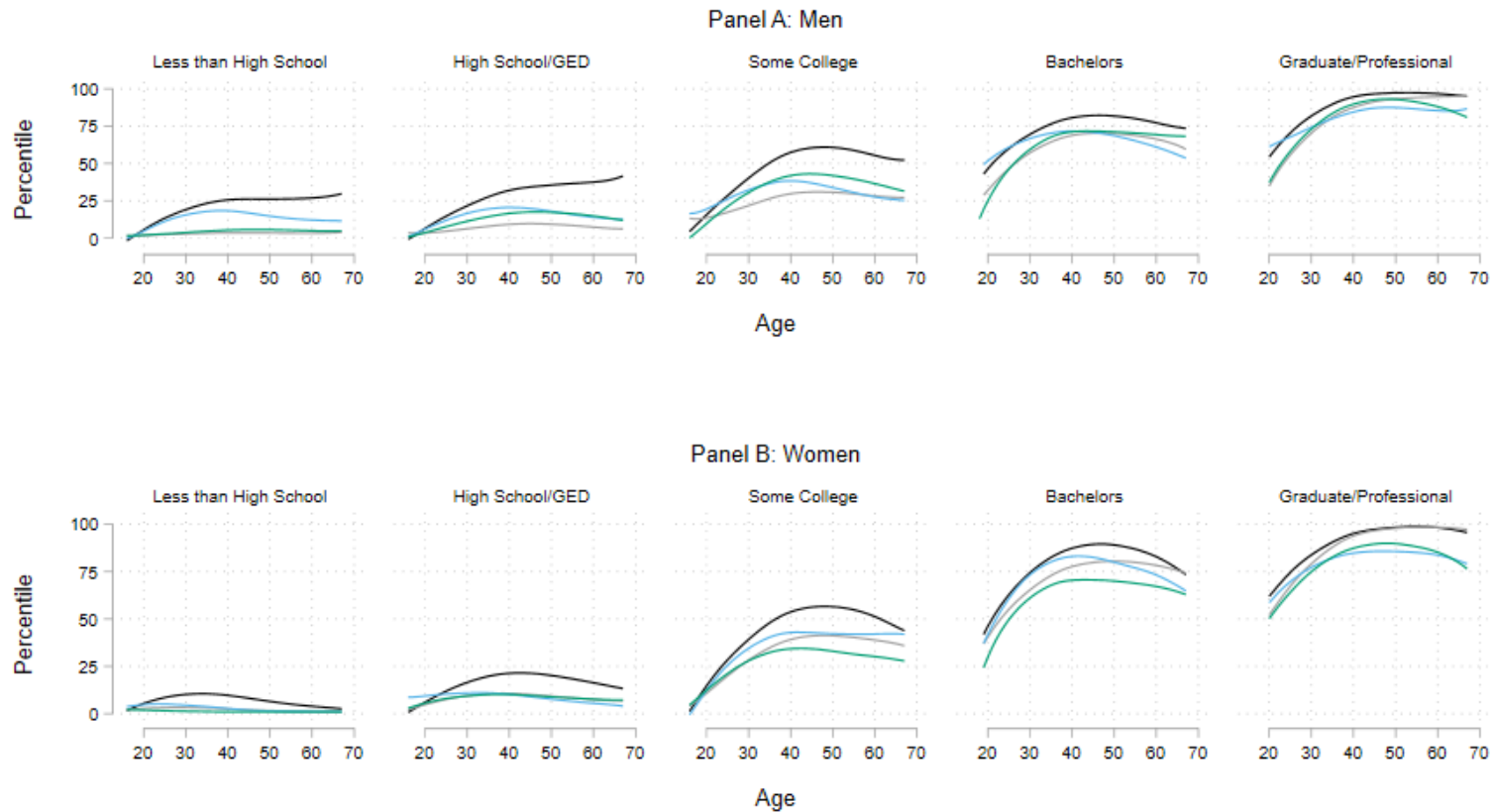
Notes: Using the combined O*NET and ACS data sets from 2004-2019 (described previously), the figure presents the relationship between social skill task intensity and age for different race/ethnicity-education groups. To create the figure, we first aggregate the data to the 1013 age-education-race/ethnicity cells, and then separate the task intensity measures into centiles (100 bins). The plotted lines rely on a LOWESS fit with the bandwidth set at 0.8.

Figure 3.17
 Nonroutine Cognitive Analytical Task Intensity and Aging
 by Gender, Race/Ethnicity, and Education



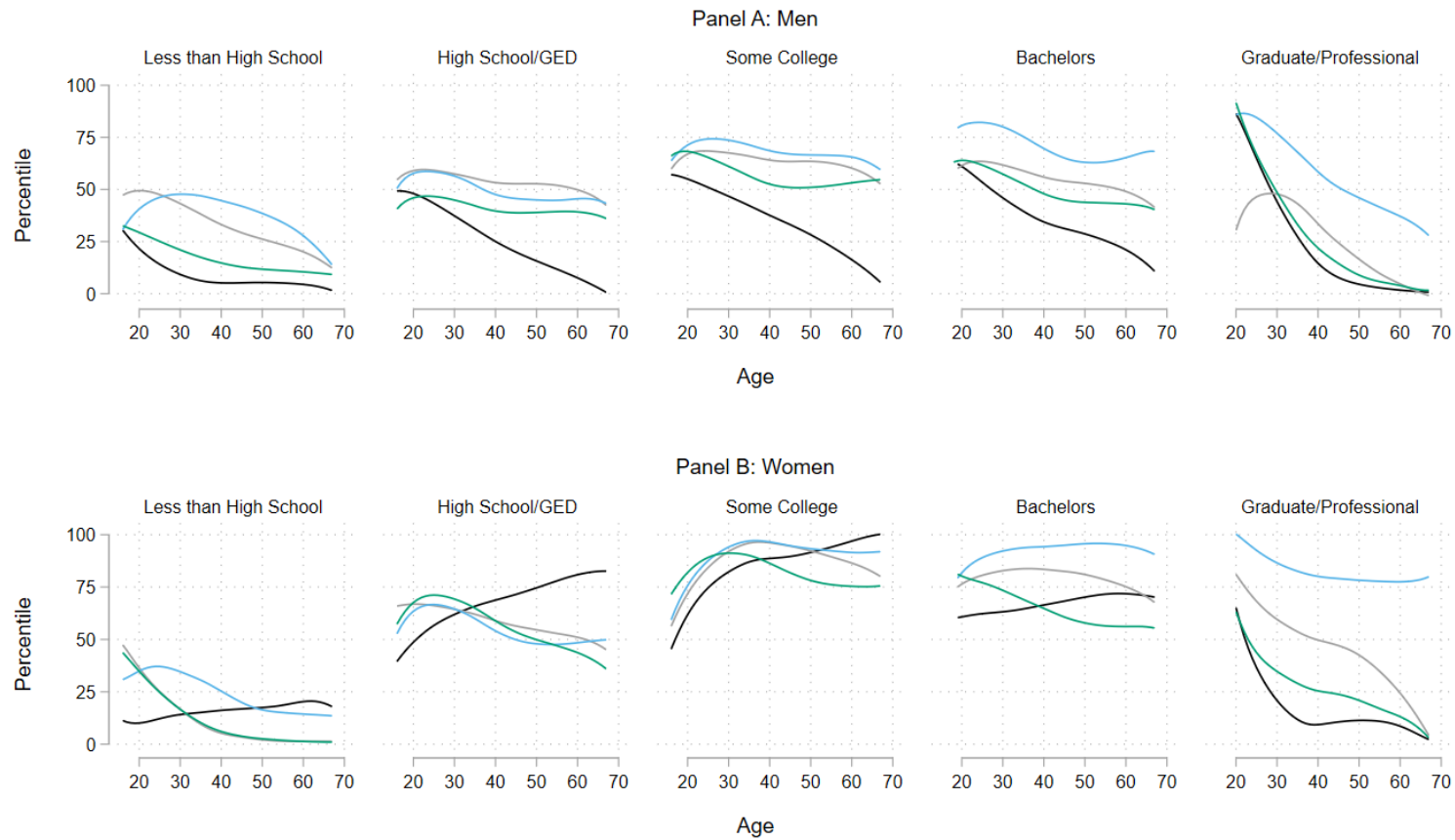
Notes: Using the combined O*NET and ACS data sets from 2004-2019 (described previously), the figure presents the relationship between social skill task intensity and age for different gender-race/ethnicity-education groups. To create the figure, we first aggregate the data to the 3533 age-education-race/ethnicity-gender cells, and then separate the task intensity measures into centiles (100 bins). The plotted lines rely on a LOWESS fit with the bandwidth set at 0.8. Panel A displays the relationships by race/ethnicity-education for men, and Panel B displays the relationships by race/ethnicity-education for women.

Figure 3.18
 Nonroutine Cognitive Interpersonal Task Intensity and Aging
 by Gender, Race/Ethnicity, and Education



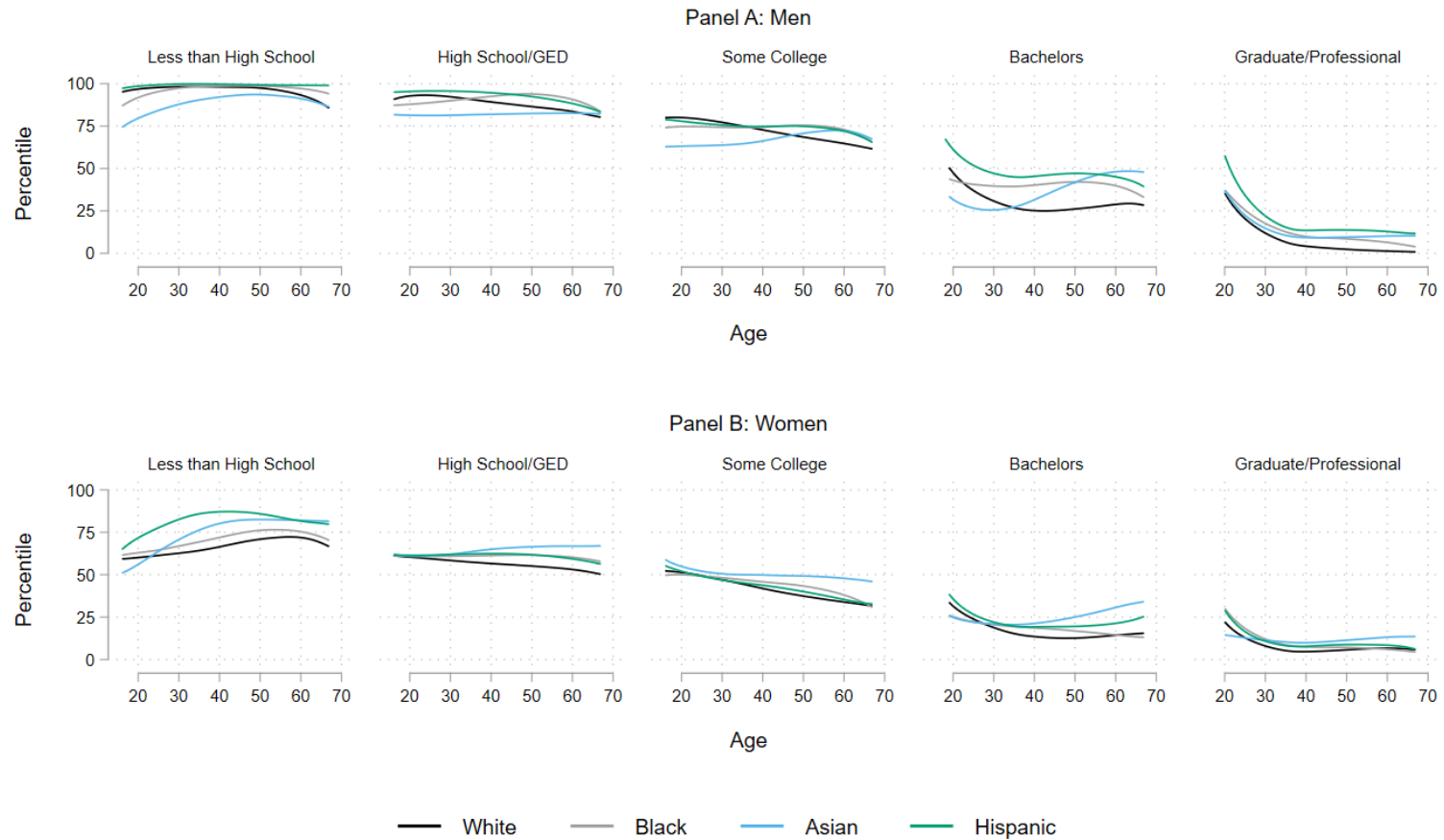
Notes: Using the combined O*NET and ACS data sets from 2004-2019 (described previously), the figure presents the relationship between social skill task intensity and age for different gender-race/ethnicity-education groups. To create the figure, we first aggregate the data to the 3533 age-education-race/ethnicity-gender cells, and then separate the task intensity measures into centiles (100 bins). The plotted lines rely on a LOWESS fit with the bandwidth set at 0.8. Panel A displays the relationships by race/ethnicity-education for men, and Panel B displays the relationships by race/ethnicity-education for women.

Figure 3.19
 Routine Cognitive Task Intensity and Aging
 by Gender, Race/Ethnicity, and Education



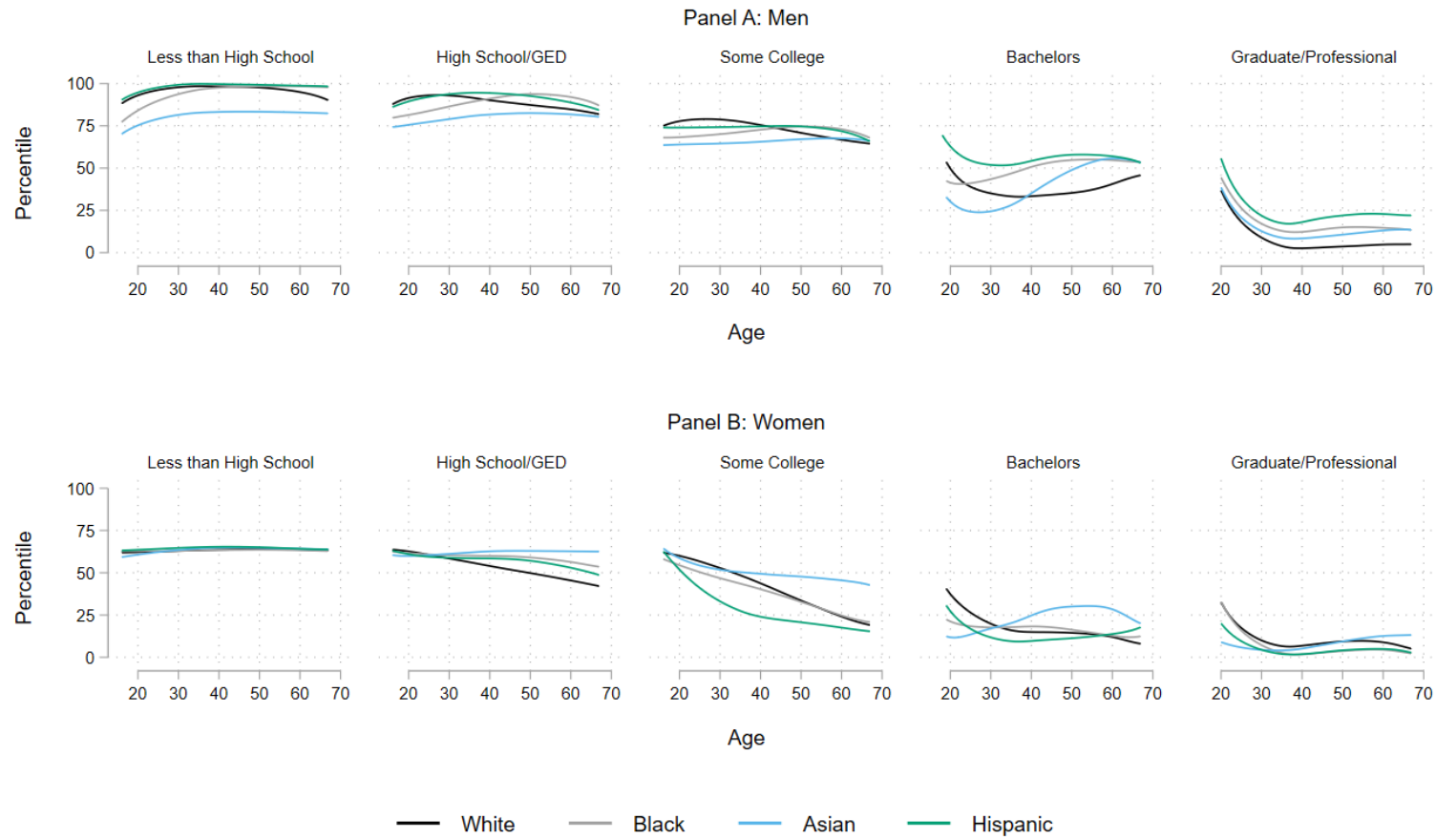
Notes: Using the combined O*NET and ACS data sets from 2004-2019 (described previously), the figure presents the relationship between social skill task intensity and age for different gender-race/ethnicity-education groups. To create the figure, we first aggregate the data to the 3533 age-education-race/ethnicity-gender cells, and then separate the task intensity measures into centiles (100 bins). The plotted lines rely on a LOWESS fit with the bandwidth set at 0.8. Panel A displays the relationships by race/ethnicity-education for men, and Panel B displays the relationships by race/ethnicity-education for women.

Figure 3.20
 Routine Manual Task Intensity and Aging
 by Gender, Race/Ethnicity, and Education



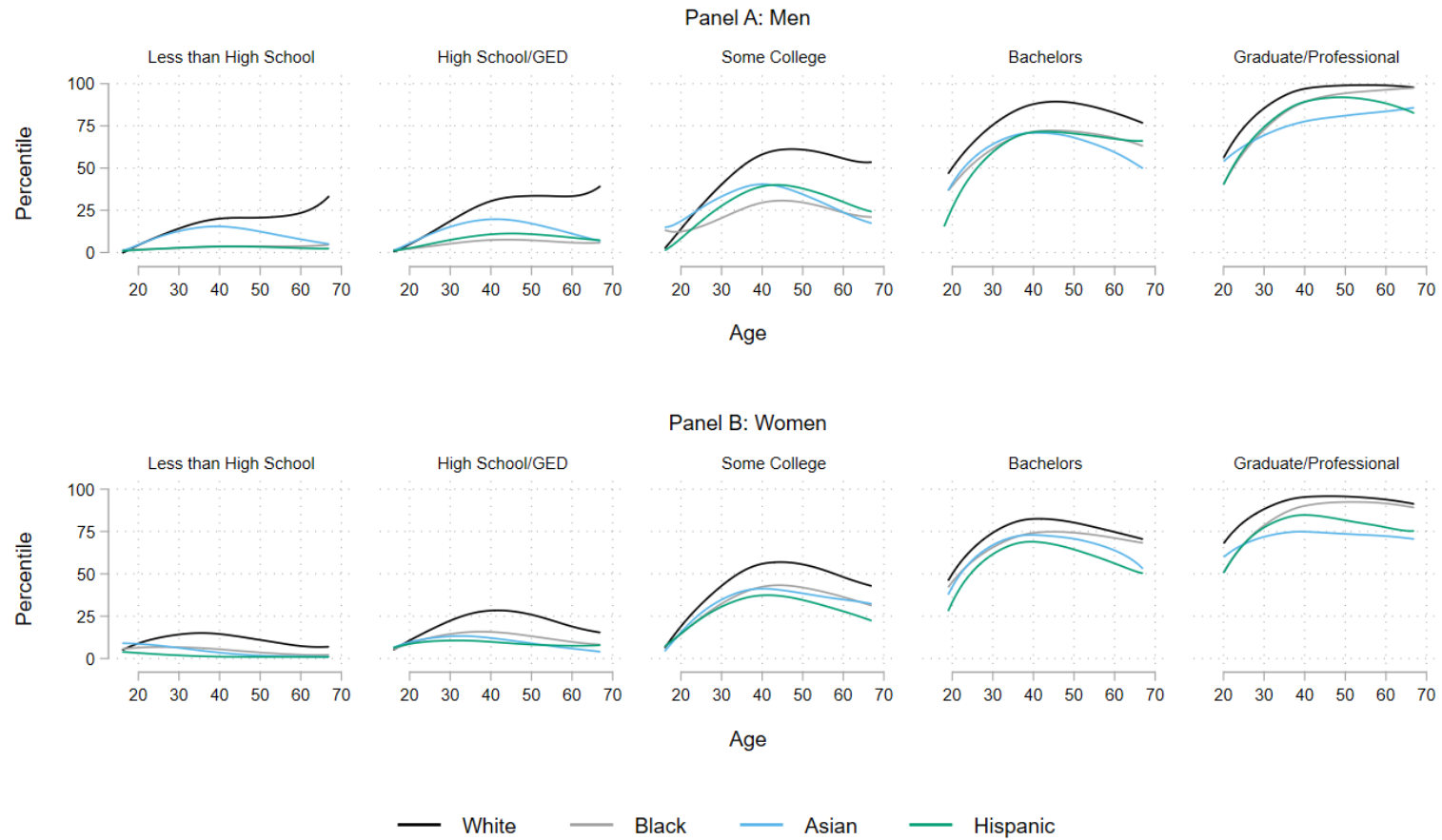
Notes: Using the combined O*NET and ACS data sets from 2004-2019 (described previously), the figure presents the relationship between social skill task intensity and age for different gender-race/ethnicity-education groups. To create the figure, we first aggregate the data to the 3533 age-education-race/ethnicity-gender cells, and then separate the task intensity measures into centiles (100 bins). The plotted lines rely on a LOWESS fit with the bandwidth set at 0.8. Panel A displays the relationships by race/ethnicity-education for men, and Panel B displays the relationships by race/ethnicity-education for women.

Figure 3.21
 Nonroutine Manual Physical Task Intensity and Aging
 by Gender, Race/Ethnicity, and Education



Notes: Using the combined O*NET and ACS data sets from 2004-2019 (described previously), the figure presents the relationship between social skill task intensity and age for different gender-race/ethnicity-education groups. To create the figure, we first aggregate the data to the 3533 age-education-race/ethnicity-gender cells, and then separate the task intensity measures into centiles (100 bins). The plotted lines rely on a LOWESS fit with the bandwidth set at 0.8. Panel A displays the relationships by race/ethnicity-education for men, and Panel B displays the relationships by race/ethnicity-education for women.

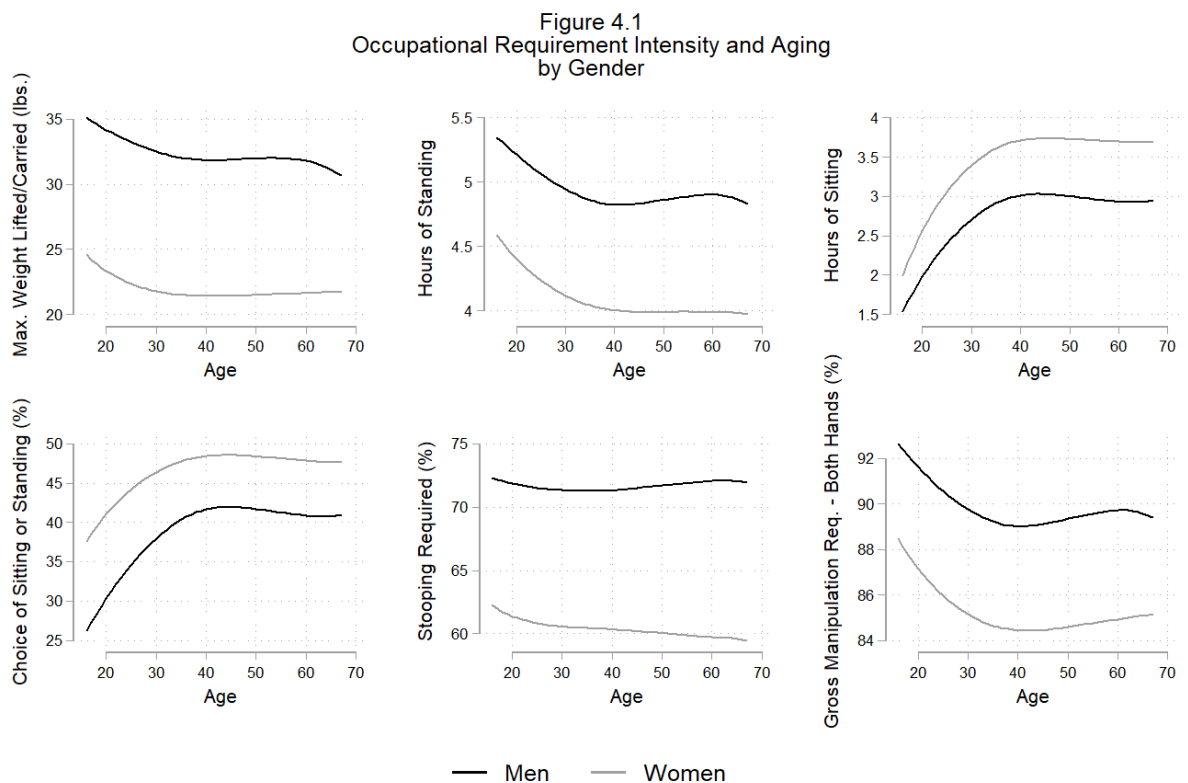
Figure 3.22
 Social Skill Task Intensity and Aging
 by Gender, Race/Ethnicity, and Education



Notes: Using the combined O*NET and ACS data sets from 2004-2019 (described previously), the figure presents the relationship between social skill task intensity and age for different gender-race/ethnicity-education groups. To create the figure, we first aggregate the data to the 3533 age-education-race/ethnicity-gender cells, and then separate the task intensity measures into centiles (100 bins). The plotted lines rely on a LOWESS fit with the bandwidth set at 0.8. Panel A displays the relationships by race/ethnicity-education for men, and Panel B displays the relationships by race/ethnicity-education for women.

4. Task-Age Profiles Using the Occupation Requirements Survey

Figure 4.1 provides the task-age plots for the six physical task measures by gender. Men disproportionately work in occupations requiring physically demanding task measures, such as maximum weight lifted/carried, standing, and gross manipulation using both hands. Young workers tend to fill occupations that require physical activities, such as lifting and carrying objects and standing. The physicality of work tends to decrease with age. The exception is stooping, which remains relatively stable as workers age.



Notes: Using the combined ORS and ACS data sets for 2018, the figure presents the relationship between the occupational requirement intensity and age for men and women. To create the figure, we first aggregate the data to the 104 age-sex cells. The plotted lines rely on a LOWESS fit with the bandwidth set at 0.8.

In Figure 4.2, we construct the task-age profiles by race/ethnicity and gender. Again, we observe race/ethnicity-gender differences similar to those from Figure 3.7. In particular, Black and Hispanic men work in occupations that are vastly more physical in nature compared to Asian and White men. Consider the requirement hours of sitting. Sixteen-year-

old men from all four categories sit for about 1.5 hours per day. By age 40, White and Asian men gain about two additional hours of sitting each day, whereas Black and Hispanic men gain only one more hour of sitting each day by the time they are 40 compared to when they were 16. Asian men tend to work in the least physically demanding occupations compared

Figure 4.2
Occupational Requirement Intensity and Aging
by Gender and Race/Ethnicity

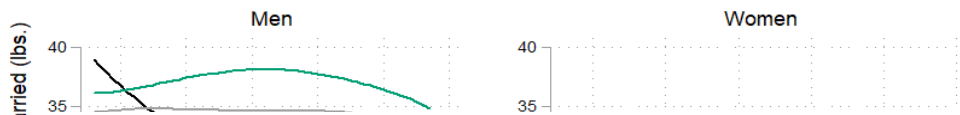
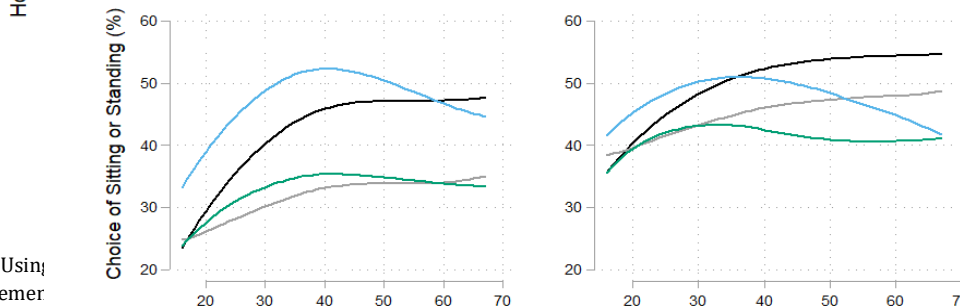
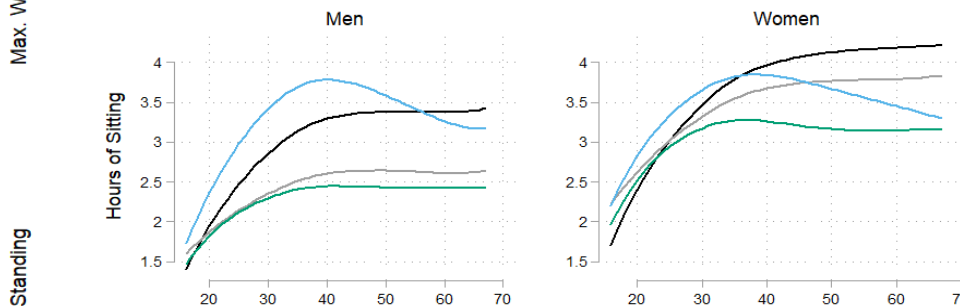


Figure 4.2 (cont.)
Occupational Requirement Intensity and Aging
by Gender and Race/Ethnicity



Notes: Using
requiremer
race/ethnic

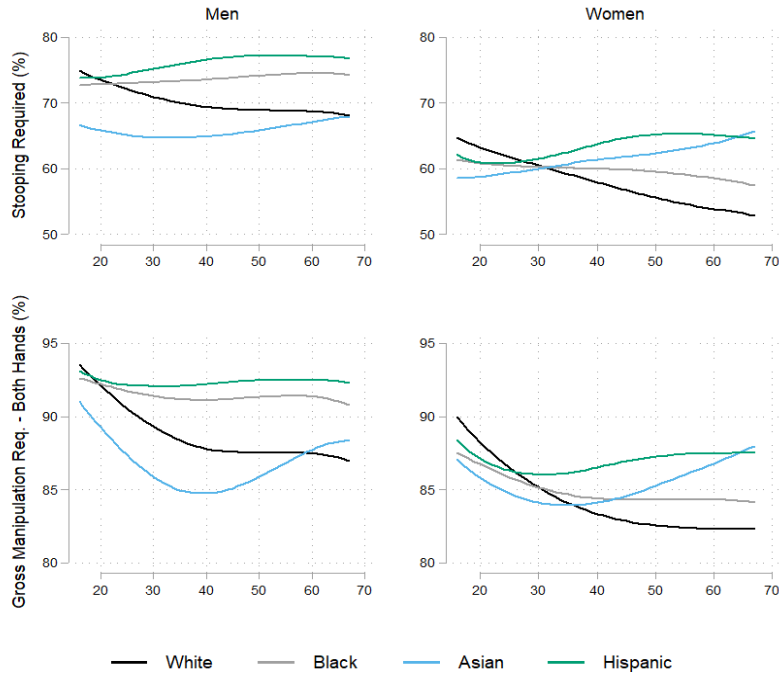
— White — Black — Asian — Hispanic

Notes: Using the combined ORS and ACS data sets for 2018, the figure presents the relationship between the occupational requirement intensity and age for different races/ethnicities. To create the figure, we first aggregate the data to 324 age-race/ethnicity cells. The plotted lines rely on a LOWESS fit with the bandwidth set at 0.8.

to the other three race/ethnicity categories. For instance, 40-year-old Hispanic men tend to spend nearly 1.5 hours more time standing each day and are subject to lifting/carrying 15 more pounds compared to Asian men of the same age. Among women, Hispanic workers tend

to work in occupations that are relatively more physically demanding than the occupations held by other racial/ethnic groups. The exception is carrying or lifting heavy items: women, regardless of race/ethnicity, lift or carry similar weighted items in their occupations.

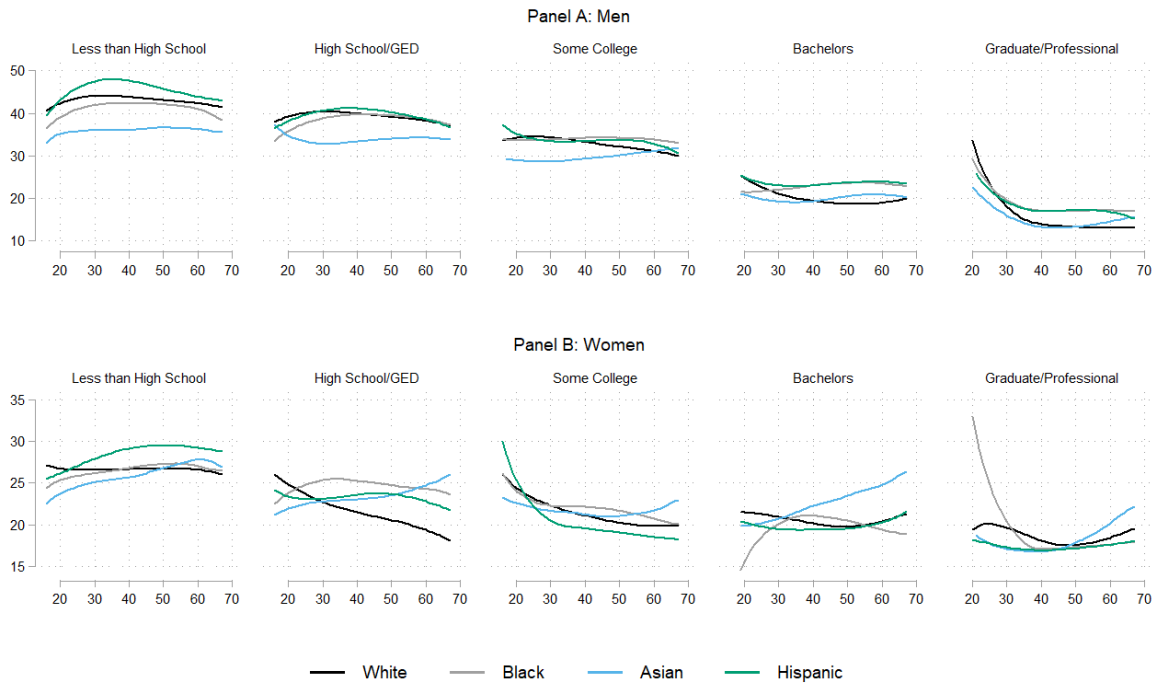
Figure 4.2 (cont.)
Occupational Requirement Intensity and Aging
by Gender and Race/Ethnicity



Notes: Using the combined ORS and ACS data sets for 2018, the figure presents the relationship between the occupational requirement intensity and age for different races/ethnicities. To create the figure, we first aggregate the data to 324 age-race/ethnicity cells. The plotted lines rely on a LOWESS fit with the bandwidth set at 0.8.

In Figure 4.3, we present task-age profiles by race/ethnicity, gender, and education group. In general, we observe similar patterns to what was observed in Figure 4.2. However, similar to Figures 3.17—3.22, we observe, for the most part, the most separation between race/ethnic groups, for both men and women, at lower education levels.

Figure 4.3
 Max. Weight Lifted/Carried (lbs.) and Aging
 by Gender, Race/Ethnicity, and Education



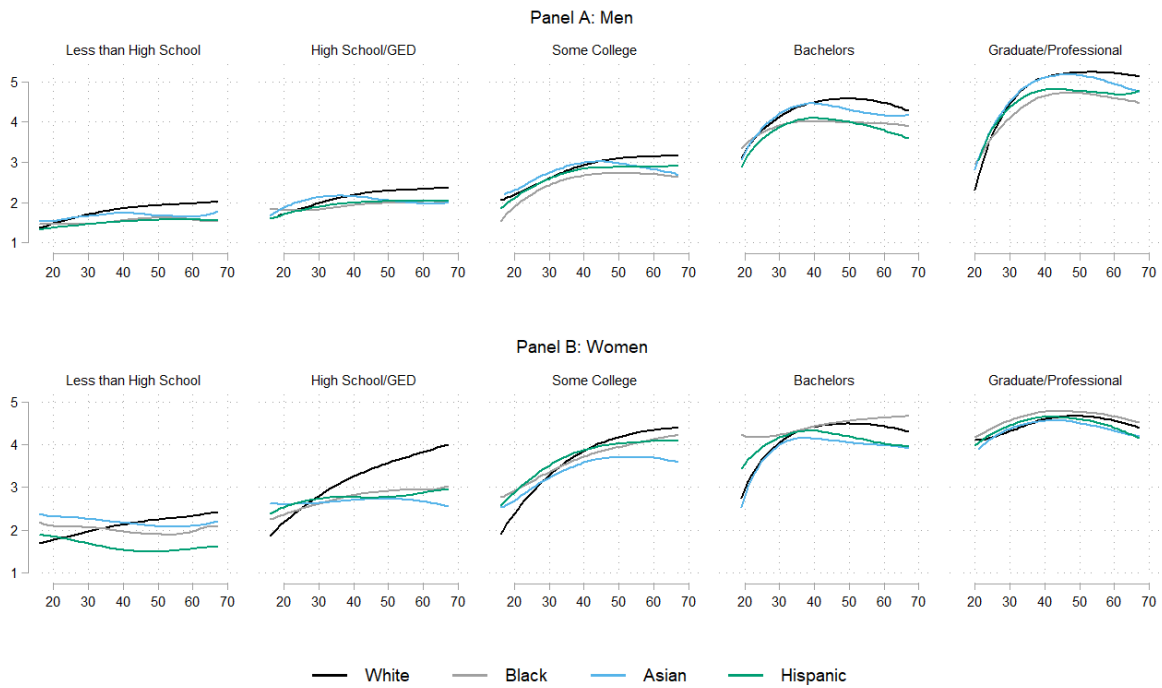
Notes: Using the combined ORS and ACS data sets for 2018, the figure presents the relationship between the occupational requirement intensity and age for different gender-race/ethnicity-education groups. To create the figure, we first aggregate the data to 2,524 age-race/ethnicity cells. The plotted lines rely on a LOWESS fit with the bandwidth set at 0.8. Panel A displays the relationships by race/ethnicity-education for men, and Panel B displays the relationships by race/ethnicity-education for women.

Figure 4.3 (cont.)
Hours of Standing and Aging
by Gender, Race/Ethnicity, and Education



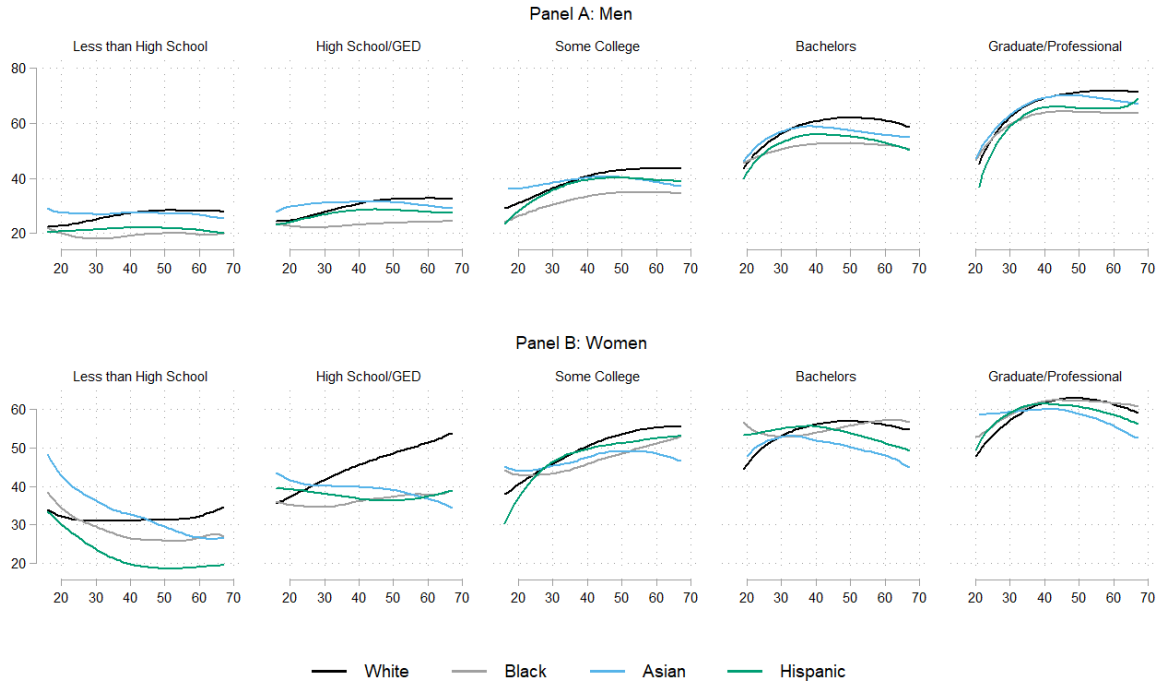
Notes: Using the combined ORS and ACS data sets for 2018, the figure presents the relationship between the occupational requirement intensity and age for different gender-race/ethnicity-education groups. To create the figure, we first aggregate the data to 2,524 age-race/ethnicity cells. The plotted lines rely on a LOWESS fit with the bandwidth set at 0.8. Panel A displays the relationships by race/ethnicity-education for men, and Panel B displays the relationships by race/ethnicity-education for women.

Figure 4.3 (cont.)
Hours of Sitting and Aging
by Gender, Race/Ethnicity, and Education



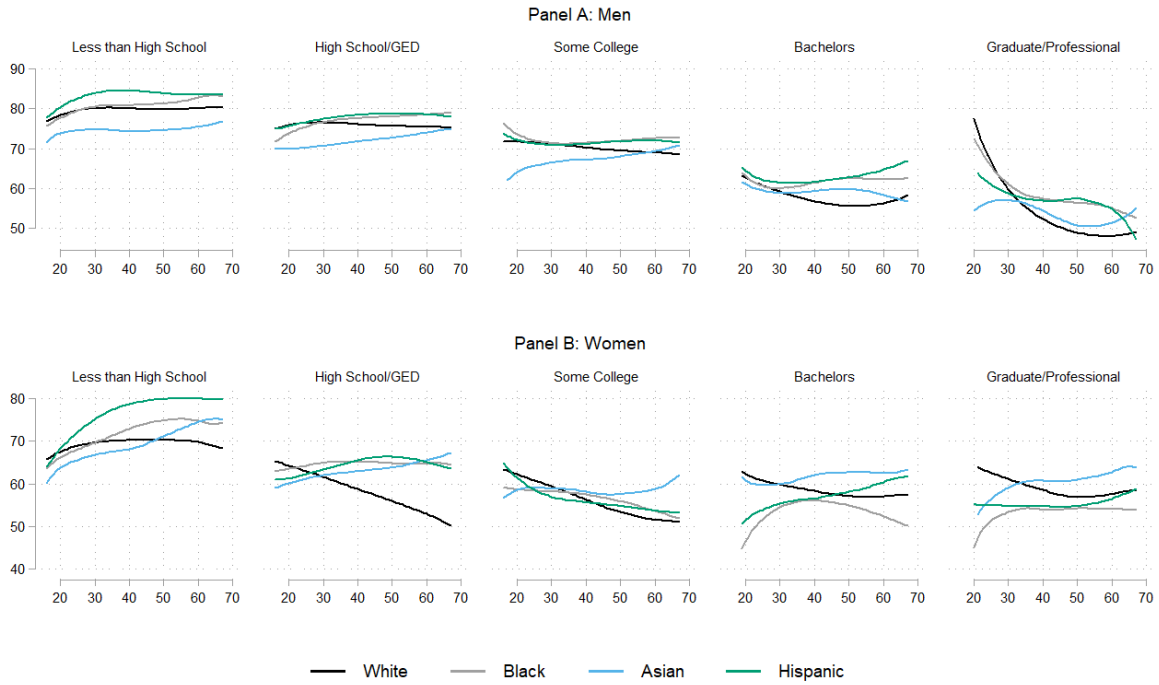
Notes: Using the combined ORS and ACS data sets for 2018, the figure presents the relationship between the occupational requirement intensity and age for different gender-race/ethnicity-education groups. To create the figure, we first aggregate the data to 2,524 age-race/ethnicity cells. The plotted lines rely on a LOWESS fit with the bandwidth set at 0.8. Panel A displays the relationships by race/ethnicity-education for men, and Panel B displays the relationships by race/ethnicity-education for women.

Figure 4.3 (cont.)
 Choice of Sitting or Standing (%) and Aging
 by Gender, Race/Ethnicity, and Education



Notes: Using the combined ORS and ACS data sets for 2018, the figure presents the relationship between the occupational requirement intensity and age for different gender-race/ethnicity-education groups. To create the figure, we first aggregate the data to 2,524 age-race/ethnicity cells. The plotted lines rely on a LOWESS fit with the bandwidth set at 0.8. Panel A displays the relationships by race/ethnicity-education for men, and Panel B displays the relationships by race/ethnicity-education for women.

Figure 4.3 (cont.)
 Stopping Required (%) and Aging
 by Gender, Race/Ethnicity, and Education



Notes: Using the combined ORS and ACS data sets for 2018, the figure presents the relationship between the occupational requirement intensity and age for different gender-race/ethnicity-education groups. To create the figure, we first aggregate the data to 2,524 age-race/ethnicity cells. The plotted lines rely on a LOWESS fit with the bandwidth set at 0.8. Panel A displays the relationships by race/ethnicity-education for men, and Panel B displays the relationships by race/ethnicity-education for women.

5. The Relationship Between Task Content and Labor Market Outcomes in the NLSY79

5.1. Wages and Weekly Hours Worked

Following the sample selection and linkage steps mentioned in Section 2.2.4., we now turn to the analysis of the NLSY79. Our examination of the NLSY79-O*NET data relies on regression analysis. The regression models involve regressing an outcome variable (e.g., wages, hours worked, etc.) on the task intensity measures along with a set of control variables and a constant term. It should be noted that our estimates should be interpreted as correlations, not necessarily causal relationships.

Table 5.1 reports log wage effects for the task variables.¹⁵ We report these models with only the skill variables as regressors (e.g., Column one), skill variables with demographic, geographic and industry controls (e.g., Column two), and models with the addition of cognitive and non-cognitive skills, as well as an indicator of physical health (e.g., Column three). Our preferred sample, which we will use for the other outcome variables, with 36,322 observations, is the one used to estimate models 2, 5, and 8 in Table 5.2. In column two, we can see that all the skill variables are associated with wage premiums, except for routine manual. For example, a one-unit increase (above the mean) in Non-Routine Cognitive Analytical intensity (NR Cognitive Analytical) corresponds to 10.7 percent increase in hourly wage. In column three, we add an Armed Forces Qualifying Test (AFQT) score, two Rotter Scales, and a categorical variable measuring general health during the respondent's youth. Adding these variables reduces the sample size substantially, although it does not significantly affect the estimates on the skill variables.

¹⁵ The estimates for the other explanatory variables in the regression models are presented in Appendix Table A1.

5.1 Impact of Task Intensity on Hourly Wage Rates

Task Variable	All			50 and Older			Younger than 50		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
NR Cognitive Analytical	0.2891** (0.0098)	0.1070** (0.0097)	0.1014** (0.0104)	0.3357** (0.0126)	0.1396** (0.0126)	0.1270** (0.0134)	0.2552** (0.0117)	0.0875** (0.0120)	0.0892** (0.0131)
NR Cognitive Interpersonal	0.0242 (0.0162)	0.0668** (0.0138)	0.0706** (0.0148)	-0.0746** (0.0255)	0.0085 (0.0226)	0.0225 (0.0239)	0.0775** (0.0178)	0.0987** (0.0159)	0.1019** (0.0171)
R Cognitive	0.1591** (0.0116)	0.0750** (0.0109)	0.0668** (0.0118)	0.1740** (0.0154)	0.0884** (0.0155)	0.0855** (0.0165)	0.1481** (0.0130)	0.0709** (0.0131)	0.0548** (0.0142)
R Manual	-0.0067 (0.0104)	-0.0117 (0.0103)	-0.0042 (0.0107)	-0.0062 (0.0132)	-0.0131 (0.0131)	-0.0110 (0.0136)	-0.0029 (0.0123)	-0.0047 (0.0127)	0.0053 (0.0133)
NR Manual Physical	0.1366** (0.0089)	0.0358** (0.0092)	0.0381** (0.0097)	0.1663** (0.0114)	0.0509** (0.0120)	0.0521** (0.0125)	0.1223** (0.0102)	0.0334** (0.0110)	0.0363** (0.0121)
Social Skill	0.1360** (0.0161)	0.0822** (0.0139)	0.0715** (0.0149)	0.2187** (0.0244)	0.1340** (0.0214)	0.1156** (0.0228)	0.0980** (0.0212)	0.0588** (0.0195)	0.0421** (0.0212)
Control Variables:									
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Industry	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Demographic	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Cognitive/ Noncognitive	No	No	Yes	No	No	Yes	No	No	Yes
Observations	36,946	36,322	30,412	18,251	17,913	15,434	18,695	18,409	14,978

Notes: The table presents the earnings returns/penalties associated with the task intensity measures. The dependent variable is the natural logarithm of the inflation-adjusted hourly wage rate (in 2018 dollars), giving the coefficient estimates a percentage change interpretation. The computed standard errors are robust to clustering on individuals and are presented in parentheses. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

Columns five and eight show substantial differences in the returns to skill by age group. A one unit increase in Social Skill is associated with a 13.4 percent increase in hourly wage for workers over age 50, whereas that same sample of workers only saw a 5.88 percent increase in wages when they were in their forties. There are several caveats to these results by age, which will also apply for subsequent models. First, the NLSY79 follows a specific birth cohort, and although we have controlled for year-fixed effects, members of the cohort were in their forties during the 2000s. Thus, the comparisons between the ages are not meant to apply contemporaneous age differences. Secondly, we do not claim there is any causal relationship implied by our estimates. For example, those who select occupations high in Social and Cognitive skills likely do so for unobserved reasons that promote wage growth. Hence, the estimates presented in this section are descriptive and tell us only about the wage premiums enjoyed by individuals who select occupations with certain task profiles.

For the sake of brevity, the rest of the regression tables in this section are presented without showing the full set of covariates.¹⁶ Following the demographic results from sections three and four, we examine the wage effects of task content for the full sub-samples of men and women workers and then by age group in Table 5.2. NR Cognitive Analytical and Social Skills are associated with significant wage premiums for all the sub-samples of men and women. However, the wage premiums are significantly higher for the older groups of workers. Non-routine Cognitive Interpersonal (NR Cognitive Interpersonal) tasks generate a wage gain for all groups, except men over age 50. Routine Cognitive (R Cognitive) and Non-Routine Manual Physical (NR Manual Physical) tasks offer wage premiums for women and men, respectively. Routine Manual (R Manual) tasks are associated with lower wages in men under age 50 and with higher wages in women over age 50.

¹⁶ The remaining tables are generated from the same sample as in model 2 of Table 5.1. The full set of results for each regression model are available upon request.

5.2 Impact of Task Intensity on Hourly Wages for Men and Women

Task Intensity Variable	Males			Females		
	All	50 and Older	Younger than 50	All	50 and Older	Younger than 50
	(1)	(2)	(3)	(4)	(5)	(6)
NR Cognitive Analytical	0.0749 ^{***} (0.0134)	0.1111 ^{***} (0.0175)	0.0549 ^{***} (0.0158)	0.1367 ^{***} (0.0144)	0.1764 ^{***} (0.0193)	0.1144 ^{***} (0.0188)
NR Cognitive Interpersonal	0.0338 [*] (0.0182)	-0.0536 [*] (0.0310)	0.0654 ^{***} (0.0166)	0.1034 ^{***} (0.0212)	0.0671 ^{**} (0.0327)	0.1311 ^{***} (0.0251)
R Cognitive	0.0193 (0.0166)	0.0303 (0.0237)	0.0242 (0.0201)	0.1116 ^{***} (0.0150)	0.1204 ^{***} (0.0211)	0.1017 ^{***} (0.0187)
R Manual	-0.0237 [*] (0.0126)	-0.0188 (0.0168)	-0.0248 [*] (0.0146)	0.0303 (0.0191)	0.0507 ^{**} (0.0242)	0.0293 (0.0249)
NR Manual Physical	0.0375 ^{***} (0.0117)	0.0655 ^{***} (0.0162)	0.0308 ^{**} (0.0135)	0.0122 (0.0172)	-0.0091 (0.0228)	0.0326 (0.0216)
Social Skill	0.0930 ^{***} (0.0184)	0.1871 ^{***} (0.0305)	0.0587 ^{***} (0.0168)	0.0679 ^{***} (0.0210)	0.0854 ^{***} (0.0297)	0.0553 [*] (0.0311)
Observations	19,296	9,349	9,947	17,026	8,564	8,462

Notes: The table presents the earnings returns/penalties associated with the task intensity measures. The dependent variable is the natural logarithm of the inflation-adjusted hourly wage rate (in 2018 dollars), giving the coefficient estimates a percentage change interpretation. Demographic controls are included in all specifications. The computed standard errors are robust to clustering on individuals and are presented in parentheses. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

In Table 5.3, the wage results are presented for sub-samples by race. Sample sizes are not sufficient to do separate analyses by race, gender, and age group. NR Cognitive Analytical tasks are associated with wage premiums for all sub-samples, while Social Skills are positively associated with wages for all sub-samples except older Hispanic people. R Cognitive tasks are associated with substantial wage gains for Black and Hispanic workers. NR Cognitive Interpersonal tasks generate positive wage gains for younger workers of all three racial groups.

In Table 5.4, we examine how labor supply at the intensive margin is related to the task variables. Unit increases in Nonroutine Cognitive Interpersonal Task Intensity and Social Task Intensity are associated with approximately 0.5—1.5 more hours worked during the week. Dramatic gender differences can be seen for R Manual Task intensity and NR Manual Physical. Women work longer hours in routine while men work more hours in non-routine manual labor, with larger effects for the over-50 sub-samples. Table 5.5 shows that Social Skills positively affect the hours worked for Black, Hispanic and White workers who are over age 50. NR Cognitive Interpersonal tasks increase hours worked for White and younger Black workers.

5.3 Impact of Task Intensity on Hourly Wages by Race/Ethnicity

Task Intensity Variable	White			Black			Hispanic		
	All	50 and Older	Younger than 50	All	50 and Older	Younger than 50	All	50 and Older	Younger than 50
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
NR Cognitive Analytical	0.0992*** (0.0130)	0.1326*** (0.0172)	0.0861*** (0.0156)	0.1271*** (0.0181)	0.1439*** (0.0252)	0.1161*** (0.0225)	0.1128*** (0.0233)	0.1609*** (0.0297)	0.0789** (0.0322)
NR Cognitive Interpersonal	0.0658*** (0.0192)	-0.0156 (0.0299)	0.1170*** (0.0186)	0.0378 (0.0257)	0.0033 (0.0476)	0.0562* (0.0294)	0.0769** (0.0304)	0.0562 (0.0501)	0.0750** (0.0380)
R Cognitive	0.0338** (0.0156)	0.0414* (0.0218)	0.0282 (0.0184)	0.1150*** (0.0191)	0.1340*** (0.0284)	0.1151*** (0.0235)	0.1294*** (0.0245)	0.1585*** (0.0334)	0.1354*** (0.0332)
R Manual	-0.0042 (0.0142)	0.0074 (0.0179)	-0.0086 (0.0177)	0.0078 (0.0196)	0.0010 (0.0277)	0.0272 (0.0237)	-0.0384 (0.0247)	-0.0622* (0.0326)	-0.0145 (0.0316)
NR Manual Physical	0.0211* (0.0124)	0.0242 (0.0159)	0.0288* (0.0151)	0.0493*** (0.0181)	0.0561** (0.0259)	0.0517** (0.0212)	0.0638*** (0.0212)	0.0941*** (0.0278)	0.0369 (0.0276)
Social Skill	0.0757*** (0.0193)	0.1489*** (0.0285)	0.0192 (0.0197)	0.1136*** (0.0254)	0.1401*** (0.0438)	0.1117*** (0.0360)	0.0582* (0.0299)	0.0722 (0.0476)	0.0864** (0.0428)
Observations	19,316	9,586	9,730	10,243	4,971	5,272	6,763	3,356	3,407

Notes: The table presents the usual hours worked in a week associated with the task intensity measures. The dependent variable is the usual hours in a week that an individual works. Demographic controls are included in all specifications. The computed standard errors are robust to clustering on individuals and are presented in parentheses. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

5.4 Impact of Task Intensity on Weekly Hours Worked

Task Intensity Variable	All			Males			Females		
	All	50 and Older	Younger than 50	All	50 and Older	Younger than 50	All	50 and Older	Younger than 50
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
NR Cognitive Analytical	0.0372 (0.1370)	0.1591 (0.1818)	-0.0885 (0.1675)	-0.3350* (0.1871)	-0.2714 (0.2524)	-0.3849* (0.2199)	0.4035** (0.1985)	0.6439** (0.2624)	0.2043 (0.2532)
NR Cognitive Interpersonal	0.7773*** (0.1839)	0.4681 (0.2942)	0.9784*** (0.2189)	0.5557** (0.2420)	0.1058 (0.4090)	0.7733*** (0.2469)	1.1253*** (0.2745)	0.8983** (0.4088)	1.4710*** (0.3329)
R Cognitive	0.0956 (0.1683)	0.2198 (0.2433)	0.0878 (0.1900)	-0.1204 (0.2581)	-0.0951 (0.3819)	-0.1048 (0.2855)	0.1172 (0.2246)	0.2310 (0.3123)	0.1108 (0.2647)
R Manual	0.0622 (0.1532)	0.0754 (0.2144)	0.0380 (0.1752)	-0.3122 (0.1937)	-0.3971 (0.2813)	-0.3205 (0.2121)	1.0212*** (0.2513)	1.3316*** (0.3296)	0.6940** (0.3391)
NR Manual Physical	0.2303 (0.1436)	0.2879 (0.1935)	0.2499 (0.1678)	0.5444*** (0.1820)	0.6921*** (0.2556)	0.5570*** (0.2109)	-0.6410** (0.2524)	-0.8310*** (0.3089)	-0.4427 (0.3406)
Social Skill	0.8963*** (0.1931)	1.1072*** (0.2968)	0.8699*** (0.2602)	1.0743*** (0.2633)	1.5010*** (0.4348)	0.8983*** (0.2517)	0.6161** (0.2777)	0.6469 (0.3941)	0.4655 (0.3890)
Observations	35,392	17,363	18,029	18,795	9,056	9,739	16,597	8,307	8,290

Notes: The table presents the usual hours worked in a week associated with the task intensity measures. The dependent variable is the usual hours in a week that an individual works. Demographic controls are included in all specifications. The computed standard errors are robust to clustering on individuals and are presented in parentheses. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

5.5 Impact of Task Intensity on Weekly Hours Worked by Race/Ethnicity

Task Intensity Variable	White			Black			Hispanic		
	All	50 and Older	Younger than 50	All	50 and Older	Younger than 50	All	50 and Older	Younger than 50
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
NR Cognitive Analytical	-0.0995 (0.1823)	0.0179 (0.2397)	-0.1934 (0.2230)	-0.1116 (0.2817)	0.1565 (0.3926)	-0.2179 (0.3447)	0.5327* (0.3105)	0.3914 (0.4194)	0.6343 (0.4056)
NR Cognitive Interpersonal	1.1366*** (0.2464)	0.9170** (0.3957)	1.2235*** (0.2930)	0.2907 (0.3832)	0.0348 (0.6800)	0.7112* (0.3687)	0.4175 (0.3752)	-0.3175 (0.6046)	0.5785 (0.4804)
R Cognitive	-0.0501 (0.2464)	0.1984 (0.3525)	-0.1853 (0.2760)	0.3349 (0.3106)	0.2062 (0.4797)	0.4755 (0.3527)	0.2104 (0.3330)	0.4826 (0.4374)	0.2085 (0.4443)
R Manual	0.1604 (0.2214)	0.2087 (0.2984)	0.0731 (0.2514)	-0.1938 (0.2762)	-0.1389 (0.3965)	-0.2373 (0.3283)	0.4956 (0.3190)	0.5679 (0.4910)	0.4999 (0.3821)
NR Manual Physical	0.0552 (0.2017)	0.2205 (0.2697)	-0.0517 (0.2336)	0.4858* (0.2878)	0.0212 (0.3963)	0.8852** (0.3477)	0.2382 (0.3014)	0.3299 (0.4294)	0.1918 (0.3786)
Social Skill	0.6512** (0.2710)	0.9162** (0.4223)	0.5549 (0.3592)	1.4134*** (0.3768)	1.4004** (0.6178)	0.9765** (0.3905)	0.6763* (0.3759)	1.3603** (0.5719)	0.8634 (0.5974)
Observations	18,894	9,319	9,575	9,922	4,791	5,131	6,576	3,253	3,323

Notes: The table presents the usual hours worked in a week associated with the task intensity measures. The dependent variable is the usual hours in a week that an individual works. Demographic controls are included in all specifications. The computed standard errors are robust to clustering on individuals and are presented in parentheses. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

5.6 Impact of 2004 Task Intensity on Weeks Out of Labor Force

Task Intensity Variable	All			Males			Females		
	All	50 and Older	Younger than 50	All	50 and Older	Younger than 50	All	50 and Older	Younger than 50
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
2004 NR Cognitive Analytical	-0.4319*** (0.0862)	-0.4829*** (0.1152)	-0.4319*** (0.0862)	-0.3476*** (0.1061)	-0.3872*** (0.1411)	-0.3261** (0.1388)	-0.4119*** (0.1463)	-0.5144** (0.2016)	-0.2527 (0.1885)
2004 NR Cognitive Interpersonal	-0.1744 (0.1223)	-0.1767 (0.1689)	-0.1744 (0.1223)	0.0056 (0.1496)	0.0357 (0.2063)	-0.0860 (0.1943)	-0.2498 (0.2035)	-0.1878 (0.2855)	-0.2169 (0.2629)
2004 R Cognitive	0.0143 (0.1030)	0.2326 (0.1427)	0.0143 (0.1030)	0.1523 (0.1468)	0.4103** (0.2032)	-0.0582 (0.1880)	-0.0582 (0.1880)	-0.1878 (0.1590)	0.0200 (0.2248)
2004 R Manual	-0.0333 (0.1057)	-0.0559 (0.1380)	-0.0333 (0.1057)	0.0056 (0.1170)	-0.1498 (0.1477)	0.0975 (0.1588)	-0.0806 (0.2249)	0.0628 (0.3196)	-0.1997 (0.2894)
2004 NR Manual Physical	0.1448* (0.0824)	0.2766** (0.1120)	0.1448* (0.0824)	0.1592* (0.0943)	0.3205** (0.1290)	-0.0078 (0.1245)	0.2804 (0.1937)	0.2859 (0.2739)	0.2606 (0.2480)
2004 Social Skill	0.1616 (0.1839)	0.5039** (0.2414)	0.1616 (0.1839)	0.2108 (0.2238)	0.3610 (0.2942)	0.1128 (0.2963)	0.1128 (0.2963)	-0.0335 (0.3037)	0.4177 (0.4051)
Observations	35,919	17,155	18,764	19,424	9,222	10,202	16,495	7,933	8,562

Notes: The table presents the weeks out of the labor force associated with the 2004 task intensity measures. The dependent variable is the number of weeks that an individual is out of the labor force in a year. Demographic controls are included in all specifications. The computed standard errors are robust to clustering on individuals and are presented in parentheses. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

5.7 Impact of Task Intensity on Weeks Out of the Labor Force by Race/Ethnicity

Task Intensity Variable	White			Black			Hispanic		
	All	50 and Older	Younger than 50	All	50 and Older	Younger than 50	All	50 and Older	Younger than 50
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
2004 NR Cognitive Analytical	-0.3305*** (0.1008)	-0.3014** (0.1455)	-0.3650*** (0.1259)	-0.3650*** (0.1259)	-0.6406*** (0.2073)	-0.7777*** (0.2902)	-0.4405 (0.2696)	-0.6229* (0.3186)	-0.2574 (0.3770)
2004 NR Cognitive Interpersonal	-0.2401* (0.1408)	-0.3272 (0.2066)	-0.1994 (0.1792)	-0.1035 (0.3023)	0.1410 (0.4114)	-0.2538 (0.3727)	0.3311 (0.3480)	0.2921 (0.4778)	0.1301 (0.4542)
2004 R Cognitive	0.0490 (0.1286)	0.1787 (0.1865)	-0.0843 (0.1560)	0.0782 (0.2041)	0.5259* (0.2847)	-0.3830 (0.2595)	-0.0642 (0.2956)	-0.1079 (0.4035)	-0.0156 (0.3630)
2004 R Manual	-0.0197 (0.1328)	0.1401 (0.1812)	-0.1796 (0.1755)	-0.0180 (0.2292)	-0.2265 (0.3029)	0.1910 (0.2962)	-0.2700 (0.3227)	-0.1657 (0.4525)	-0.1448 (0.4095)
2004 NR Manual Physical	0.0198 (0.1008)	0.0484 (0.1430)	-0.0418 (0.1329)	0.3024* (0.1819)	0.6053** (0.2529)	0.0748 (0.2283)	0.1969 (0.2262)	0.1781 (0.3184)	0.1725 (0.2880)
2004 Social Skill	0.0912 (0.2238)	0.4883 (0.3112)	-0.2572 (0.2988)	0.3088 (0.4126)	0.5313 (0.5561)	0.0652 (0.5327)	-0.3270 (0.5225)	0.1529 (0.6541)	-0.4045 (0.7007)
Observations	18,894	9,082	9,812	10,443	4,922	5,521	6,582	3,151	3,431

Notes: The table presents the usual hours worked in a week associated with the 2004 task intensity measures. The dependent variable is the number of weeks that an individual is out of the labor force in a year. Demographic controls are included in all specifications. The computed standard errors are robust to clustering on individuals and are presented in parentheses. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

5.2. Weeks Out of the Labor Force

We now turn to an analysis of labor supply response, at the extensive margin, to task intensities in our base year, 2004. Table 5.6 shows how weeks out of labor (since date of last interview) responds to task intensity. A unit increase in Non-Routine Cognitive Analytical intensity in 2004 (2004 NR Cognitive Analytical) reduces weeks out of the labor force for all sub-groups, except for women under age 50. Non-Routine Manual Physical intensity (2004 NR Manual Physical) increases weeks out of the labor force for the full sample, although this result appears to be driven by men over age 50, with an approximate one third of an additional week out of the workforce for each unit increase in the task's intensity. Social Skill intensity generates half a week out of the labor force for respondents in their fifties but the effects are not statistically significant for the sub-samples of men and women.

Table 5.7 shows the same models from Table 5.6 by race/ethnicity. NR Cognitive Analytical tasks are negatively associated with weeks spent out of the labor force, except for younger Hispanic workers. Older Black workers are more likely to spend time out of the labor force for occupations higher in NR Manual Physical and R Cognitive tasks, in 2004. For each unit increase in NR Manual Physical and R Cognitive tasks, Black workers over 50 spend approximately 0.6 and 0.5, respectively, more weeks out of the labor force.

5.3. Occupation Switching

We make further use of the work histories in the NLSY79 by examining the effects of task intensity on occupational switching. Table 5.8 reports the effects of linear probability models in which changing your primary occupation (overall, within firm, or outside of firm) from the previous survey is the outcome of interest. NR Cognitive Analytical intensity decreases the probability of switching occupations, an effect that appears to be driven by people not switching occupations and going to another firm. For example, in Column eight, workers over age 50 are 1.78 percentage points less likely to leave their firm for another occupation in response to a one-unit increase in NR Cognitive Analytical intensity. NR Cognitive Interpersonal intensity increases the probability of an occupational switch, although this seems to be driven by the effect on older workers switching to a different occupation within

5.8 Impact of Task Intensity of Last Occupation on Switching Occupations

Task Intensity Variable	Any Switch			Switch Within Firm			Switch Outside of Firm		
	All	50 and Older	Younger than 50	All	50 and Older	Younger than 50	All	50 and Older	Younger than 50
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
NR Cognitive Analytical	-0.0168*** (0.0045)	-0.0149** (0.0059)	-0.0130* (0.0068)	0.0007 (0.0033)	0.0028 (0.0046)	0.0011 (0.0046)	-0.0175*** (0.0035)	-0.0178*** (0.0045)	-0.0141** (0.0056)
NR Cognitive Interpersonal	0.0165*** (0.0060)	0.0245*** (0.0087)	0.0175** (0.0086)	0.0122*** (0.0043)	0.0176*** (0.0062)	0.0079 (0.0059)	0.0043 (0.0049)	0.0069 (0.0070)	0.0097 (0.0071)
R Cognitive	0.0095* (0.0049)	0.0197*** (0.0065)	-0.0032 (0.0070)	0.0082** (0.0034)	0.0095** (0.0047)	0.0056 (0.0046)	0.0013 (0.0040)	0.0102* (0.0052)	-0.0088 (0.0059)
R Manual	0.0199*** (0.0048)	0.0247*** (0.0062)	0.0047 (0.0070)	0.0130*** (0.0033)	0.0187*** (0.0044)	0.0020 (0.0044)	0.0069* (0.0038)	0.0060 (0.0050)	0.0027 (0.0060)
NR Manual Physical	-0.0226*** (0.0042)	-0.0213*** (0.0056)	-0.0232*** (0.0060)	-0.0126*** (0.0029)	-0.0123*** (0.0040)	-0.0139*** (0.0039)	-0.0100*** (0.0034)	-0.0090** (0.0044)	-0.0093* (0.0052)
Social Skill	-0.0061 (0.0063)	-0.0029 (0.0085)	-0.0367*** (0.0109)	-0.0048 (0.0044)	-0.0047 (0.0059)	-0.0152** (0.0073)	0.0018 (0.0068)	-0.0215** (0.0091)	0.0018 (0.0068)
Observations	29,838	17,145	12,693	29,838	17,145	12,693	29,838	17,145	12,693

Notes: The table presents the probability of switching jobs associated with the previous period's task intensity measures. The dependent variable is equal to one if that an individual has switched jobs, giving the coefficient estimates a percentage point interpretation. Demographic controls are included in all specifications. The computed standard errors are robust to clustering on individuals and are presented in parentheses. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

firm. NR Manual intensity decreases the probability of switching occupations in all sub-samples. Routine Manual intensity appears to affect older workers who switch occupations within their firm.

Tables 5.9 and 5.10 repeat the analysis in Table 5.8, with sub-samples of men and women. NR Cognitive Analytical intensity decreases the probability of women switching occupations, primarily by not switching occupations and going to another firm, while men are largely unaffected. NR Cognitive Interpersonal intensity increases the probability of occupational switch for older men and women but not for the under-50 sub-sample. Routine Manual intensity increases the probability of occupational switch for both men and women who are 50 and over but not for the younger sub-sample. Non-Routine Manual intensity has a negative effect on occupational switching for both men and women.

5.9 Impact of Task Intensity of Last Occupation on Switching Occupations for Male Workers

Task Intensity Variable	Any Switch			Switch Within Firm			Switch Outside of Firm		
	All	50 and Older	Younger than 50	All	50 and Older	Younger than 50	All	50 and Older	Younger than 50
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
NR Cognitive Analytical	-0.0079 (0.0062)	-0.0105 (0.0080)	0.0015 (0.0094)	-0.0032 (0.0044)	-0.0043 (0.0060)	0.0005 (0.0063)	-0.0048 (0.0048)	-0.0061 (0.0061)	0.0010 (0.0078)
NR Cognitive Interpersonal	0.0143* (0.0080)	0.0165 (0.0116)	0.0189 (0.0116)	0.0130** (0.0055)	0.0185** (0.0078)	0.0045 (0.0080)	0.0013 (0.0068)	-0.0020 (0.0098)	0.0145 (0.0097)
R Cognitive	0.0127* (0.0073)	0.0175* (0.0099)	0.0041 (0.0108)	0.0081 (0.0050)	0.0131* (0.0069)	-0.0006 (0.0071)	0.0046 (0.0060)	0.0044 (0.0079)	0.0047 (0.0091)
R Manual	0.0184*** (0.0059)	0.0229*** (0.0077)	0.0070 (0.0090)	0.0088** (0.0038)	0.0139*** (0.0053)	-0.0003 (0.0055)	0.0096** (0.0048)	0.0089 (0.0063)	0.0074 (0.0078)
NR Manual Physical	-0.0183*** (0.0052)	-0.0181** (0.0072)	-0.0200*** (0.0077)	-0.0109*** (0.0035)	-0.0090* (0.0049)	-0.0135*** (0.0049)	-0.0074* (0.0043)	-0.0090 (0.0060)	-0.0064 (0.0067)
Social Skill	-0.0055 (0.0085)	0.0009 (0.0117)	-0.0368** (0.0148)	-0.0050 (0.0055)	-0.0014 (0.0074)	-0.0149 (0.0099)	-0.0004 (0.0071)	0.0022 (0.0100)	-0.0220* (0.0125)
Observations	15,987	9,094	6,893	15,987	9,094	6,893	15,987	9,094	6,893

Notes: The table presents the probability of switching jobs associated with the previous period's task intensity measures for males. The dependent variable is equal to one if that an individual has switched jobs, giving the coefficient estimates a percentage point interpretation. Demographic controls are included in all specifications. The computed standard errors are robust to clustering on individuals and are presented in parentheses. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

5.10 Impact of Task Intensity of Last Occupation on Switching Occupations for Female Workers

Task Intensity Variable	Any Switch			Switch Within Firm			Switch Outside of Firm		
	All	50 and Older	Younger than 50	All	50 and Older	Younger than 50	All	50 and Older	Younger than 50
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
NR Cognitive Analytical	-0.0233*** (0.0069)	-0.0159* (0.0091)	-0.0258** (0.0106)	0.0064 (0.0052)	0.0136* (0.0072)	0.0014 (0.0072)	-0.0297*** (0.0054)	-0.0295*** (0.0071)	-0.0272*** (0.0087)
NR Cognitive Interpersonal	0.0219** (0.0096)	0.0371*** (0.0140)	0.0148 (0.0135)	0.0107 (0.0070)	0.0133 (0.0104)	0.0077 (0.0093)	0.0111 (0.0076)	0.0238** (0.0111)	0.0072 (0.0110)
R Cognitive	0.0056 (0.0069)	0.0193** (0.0092)	-0.0084 (0.0102)	0.0064 (0.0050)	0.0056 (0.0069)	0.0112 (0.0069)	-0.0009 (0.0056)	0.0137* (0.0073)	-0.0196** (0.0086)
R Manual	0.0268*** (0.0088)	0.0373*** (0.0116)	0.0044 (0.0127)	0.0210*** (0.0064)	0.0303*** (0.0087)	0.0026 (0.0084)	0.0058 (0.0070)	0.0070 (0.0093)	0.0018 (0.0108)
NR Manual Physical	-0.0359*** (0.0081)	-0.0392*** (0.0101)	-0.0309*** (0.0119)	-0.0205*** (0.0058)	-0.0247*** (0.0080)	-0.0130* (0.0077)	-0.0155** (0.0064)	-0.0145* (0.0077)	-0.0180* (0.0100)
Social Skill	-0.0095 (0.0098)	-0.0113 (0.0130)	-0.0344** (0.0174)	-0.0065 (0.0072)	-0.0069 (0.0096)	-0.0114 (0.0118)	-0.0029 (0.0077)	-0.0045 (0.0100)	-0.0230 (0.0142)
Observations	13,851	8,051	5,800	13,851	8,051	5,800	13,851	8,051	5,800

Notes: The table presents the probability of switching jobs associated with the previous period's task intensity measures for females. The dependent variable is equal to one if that an individual has switched jobs, giving the coefficient estimates a percentage point interpretation. Demographic controls are included in all specifications. The computed standard errors are robust to clustering on individuals and are presented in parentheses. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

Tables 5.11, 5.12, and 5.13 show results for the job-switching outcomes for White, Black and Hispanic workers, respectively. NR Cognitive Analytical intensity is negatively related to occupational switching for White workers switching occupations outside their firm. NR Cognitive Interpersonal intensity is associated with occupational switching for older White and Black workers. NR Manual Physical intensity is negatively associated with occupational switching for all racial/ethnic sub-groups, particularly within the firm.

5.4. Holding Multiple Jobs

Table 5.14 shows results for linear probability models of the impact of task intensities on the probability a worker will hold multiple jobs at the same time. We find little evidence that tasks of specific occupations drive the common decision (in the NLSY79) to work multiple jobs, with the exception of NR Cognitive Analytical intensity decreasing the probability of holding multiple jobs in younger men by 1.89 percentage points. Table 5.15 shows that NR Cognitive Analytical and NR Manual Physical intensity have negative effects on holding multiple jobs among young White and Hispanic workers, respectively.

5.11 Impact of Task Intensity of Last Occupation on Switching Occupations for White Workers

Task Intensity Variable	Any Switch			Switch Within Firm			Switch Outside of Firm		
	All	50 and Older	Younger than 50	All	50 and Older	Younger than 50	All	50 and Older	Younger than 50
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
NR Cognitive Analytical	-0.0289*** (0.0059)	-0.0306*** (0.0077)	-0.0280*** (0.0090)	-0.0062 (0.0043)	-0.0087 (0.0058)	-0.0059 (0.0062)	-0.0227*** (0.0044)	-0.0219*** (0.0059)	-0.0220*** (0.0073)
NR Cognitive Interpersonal	0.0225*** (0.0079)	0.0406*** (0.0115)	0.0137 (0.0112)	0.0176*** (0.0057)	0.0326*** (0.0080)	0.0026 (0.0079)	0.0049 (0.0065)	0.0080 (0.0095)	0.0110 (0.0091)
R Cognitive	-0.0005 (0.0069)	0.0099 (0.0096)	-0.0094 (0.0099)	0.0076 (0.0049)	0.0094 (0.0069)	0.0080 (0.0069)	-0.0081 (0.0056)	0.0005 (0.0077)	-0.0175** (0.0084)
R Manual	0.0169** (0.0068)	0.0273*** (0.0092)	-0.0040 (0.0099)	0.0111** (0.0047)	0.0196*** (0.0068)	-0.0029 (0.0060)	0.0058 (0.0055)	0.0076 (0.0071)	-0.0010 (0.0084)
NR Manual Physical	-0.0233*** (0.0061)	-0.0260*** (0.0082)	-0.0232*** (0.0086)	-0.0148*** (0.0042)	-0.0156*** (0.0060)	-0.0176*** (0.0054)	-0.0085* (0.0048)	-0.0104 (0.0064)	-0.0056 (0.0073)
Social Skill	-0.0085 (0.0086)	-0.0118 (0.0116)	-0.0256* (0.0150)	-0.0082 (0.0061)	-0.0133* (0.0080)	-0.0069 (0.0101)	-0.0003 (0.0070)	0.0016 (0.0096)	-0.0188 (0.0123)
Observations	15,973	9,200	6,773	15,973	9,200	6,773	15,973	9,200	6,773

Notes: The table presents the probability of switching jobs associated with the previous period's task intensity measures. The dependent variable is equal to one if that an individual has switched jobs, giving the coefficient estimates a percentage point interpretation. Demographic controls are included in all specifications. The computed standard errors are robust to clustering on individuals and are presented in parentheses. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

5.12 Impact of Task Intensity of Last Occupation on Switching Occupations for Black Workers

Task Intensity Variable	Any Switch			Switch Within Firm			Switch Outside of Firm		
	All	50 and Older	Younger than 50	All	50 and Older	Younger than 50	All	50 and Older	Younger than 50
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
NR Cognitive Analytical	-0.0041 (0.0096)	0.0055 (0.0128)	-0.0017 (0.0146)	0.0069 (0.0075)	0.0187* (0.0106)	0.0009 (0.0094)	-0.0110 (0.0077)	-0.0131 (0.0098)	-0.0026 (0.0123)
NR Cognitive Interpersonal	0.0111 (0.0135)	0.0040 (0.0189)	0.0260 (0.0200)	0.0069 (0.0075)	0.0187* (0.0106)	0.0009 (0.0094)	0.0075 (0.0111)	0.0040 (0.0147)	0.0145 (0.0172)
R Cognitive	0.0241*** (0.0087)	0.0292** (0.0119)	0.0162 (0.0138)	0.0054 (0.0063)	0.0066 (0.0092)	0.0030 (0.0093)	0.0187** (0.0074)	0.0226** (0.0098)	0.0131 (0.0117)
R Manual	0.0219** (0.0087)	0.0405*** (0.0116)	-0.0052 (0.0136)	0.0132** (0.0059)	0.0183** (0.0081)	-0.0007 (0.0085)	0.0086 (0.0074)	0.0222** (0.0099)	-0.0045 (0.0121)
NR Manual Physical	-0.0250*** (0.0080)	-0.0277*** (0.0107)	-0.0212* (0.0121)	-0.0123** (0.0055)	-0.0109 (0.0077)	-0.0131* (0.0078)	-0.0127* (0.0068)	-0.0168* (0.0090)	-0.0081 (0.0109)
Social Skill	-0.0059 (0.0127)	0.0086 (0.0169)	-0.0553** (0.0230)	-0.0004 (0.0087)	0.0021 (0.0124)	-0.0223 (0.0148)	-0.0054 (0.0104)	0.0065 (0.0133)	-0.0330* (0.0198)
Observations	8,351	4,737	3,614	8,351	4,737	3,614	8,351	4,737	3,614

Notes: The table presents the probability of switching jobs associated with the previous period's task intensity measures. The dependent variable is equal to one if that an individual has switched jobs, giving the coefficient estimates a percentage point interpretation. Demographic controls are included in all specifications. The computed standard errors are robust to clustering on individuals and are presented in parentheses. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

5.13 Impact of Task Intensity of Last Occupation on Switching Occupations for Hispanic Workers

Task Intensity Variable	Any Switch			Switch Within Firm			Switch Outside of Firm		
	All	50 and Older	Younger than 50	All	50 and Older	Younger than 50	All	50 and Older	Younger than 50
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
NR Cognitive Analytical	-0.0096 (0.0112)	-0.0083 (0.0146)	0.0077 (0.0185)	0.0075 (0.0079)	0.0082 (0.0111)	0.0204 (0.0127)	-0.0171* (0.0091)	-0.0165 (0.0118)	-0.0127 (0.0155)
NR Cognitive Interpersonal	0.0027 (0.0144)	0.0088 (0.0221)	0.0041 (0.0220)	0.0078 (0.0100)	0.0058 (0.0159)	0.0114 (0.0149)	-0.0051 (0.0117)	0.0030 (0.0180)	-0.0073 (0.0183)
R Cognitive	0.0063 (0.0117)	0.0316** (0.0151)	-0.0300* (0.0181)	0.0119 (0.0079)	0.0127 (0.0107)	0.0063 (0.0109)	-0.0056 (0.0095)	0.0189 (0.0118)	-0.0363** (0.0158)
R Manual	0.0242* (0.0125)	0.0041 (0.0162)	0.0382* (0.0200)	0.0183** (0.0088)	0.0167 (0.0110)	0.0156 (0.0127)	0.0060 (0.0099)	-0.0127 (0.0129)	0.0226 (0.0178)
NR Manual Physical	-0.0257** (0.0103)	-0.0141 (0.0131)	-0.0364** (0.0157)	-0.0133* (0.0075)	-0.0168* (0.0094)	-0.0130 (0.0105)	-0.0125 (0.0081)	0.0027 (0.0102)	-0.0234 (0.0143)
Social Skill	0.0018 (0.0150)	0.0071 (0.0210)	-0.0432 (0.0282)	-0.0048 (0.0103)	-0.0023 (0.0145)	-0.0262 (0.0184)	0.0066 (0.0121)	0.0094 (0.0169)	-0.0170 (0.0239)
Observations	5,514	3,208	2,306	5,514	3,208	2,306	5,514	3,208	2,306

Notes: The table presents the probability of switching jobs associated with the previous period's task intensity measures. The dependent variable is equal to one if that an individual has switched jobs, giving the coefficient estimates a percentage point interpretation. Demographic controls are included in all specifications. The computed standard errors are robust to clustering on individuals and are presented in parentheses. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

5.14 Impact of Task Intensity on Working Multiple Jobs

Task Intensity Variable	All			Males			Females		
	All	50 and Older	Younger than 50	All	50 and Older	Younger than 50	All	50 and Older	Younger than 50
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
NR Cognitive Analytical	-0.0056 (0.0036)	-0.0057 (0.0047)	-0.0056 (0.0046)	-0.0132*** (0.0051)	-0.0051 (0.0072)	-0.0189*** (0.0062)	0.0048 (0.0053)	-0.0014 (0.0065)	0.0093 (0.0071)
NR Cognitive Interpersonal	0.0009 (0.0046)	0.0069 (0.0076)	-0.0008 (0.0054)	0.0034 (0.0068)	0.0047 (0.0113)	0.0072 (0.0063)	-0.0047 (0.0065)	0.0070 (0.0106)	-0.0076 (0.0076)
R Cognitive	0.0027 (0.0042)	0.0038 (0.0057)	0.0015 (0.0051)	0.0115* (0.0068)	0.0099 (0.0095)	0.0150* (0.0079)	-0.0040 (0.0055)	0.0001 (0.0074)	-0.0087 (0.0072)
R Manual	-0.0008 (0.0037)	0.0004 (0.0047)	-0.0027 (0.0043)	-0.0005 (0.0046)	0.0017 (0.0060)	-0.0060 (0.0052)	-0.0019 (0.0064)	-0.0019 (0.0091)	-0.0031 (0.0078)
NR Manual Physical	-0.0012 (0.0038)	-0.0054 (0.0050)	0.0016 (0.0044)	-0.0039 (0.0050)	-0.0063 (0.0065)	-0.0007 (0.0057)	0.0031 (0.0068)	-0.0014 (0.0096)	0.0047 (0.0080)
Social Skill	0.0037 (0.0048)	-0.0027 (0.0075)	0.0050 (0.0066)	0.0078 (0.0070)	0.0030 (0.0112)	0.0036 (0.0058)	-0.0008 (0.0067)	-0.0106 (0.0100)	-0.0009 (0.0096)
Observations	36,322	17,913	18,409	19,296	9,349	9,947	17,026	8,564	8,462

Notes: The table presents the probability of holding multiple jobs associated with the task intensity measures. The dependent variable is equal to one if that an individual is holding multiple jobs, giving the coefficient estimates a percentage point interpretation. Demographic controls are included in all specifications. The computed standard errors are robust to clustering on individuals and are presented in parentheses. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

5.15 Impact of Task Intensity on Working Multiple Jobs by Race/Ethnicity

Task Intensity Variable	White			Black			Hispanic		
	All	50 and Older	Younger than 50	All	50 and Older	Younger than 50	All	50 and Older	Younger than 50
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
NR Cognitive Analytical	-0.0084* (0.0049)	-0.0051 (0.0065)	-0.0122** (0.0061)	-0.0027 (0.0081)	-0.0077 (0.0098)	0.0039 (0.0103)	-0.0026 (0.0077)	-0.0034 (0.0101)	-0.0002 (0.0109)
NR Cognitive Interpersonal	0.0008 (0.0059)	0.0089 (0.0096)	-0.0037 (0.0071)	0.0007 (0.0105)	0.0096 (0.0176)	-0.0006 (0.0097)	-0.0033 (0.0101)	-0.0038 (0.0176)	-0.0048 (0.0115)
R Cognitive	0.0006 (0.0060)	0.0024 (0.0081)	-0.0000 (0.0074)	0.0104 (0.0083)	0.0136 (0.0115)	0.0032 (0.0103)	-0.0039 (0.0076)	-0.0010 (0.0108)	-0.0086 (0.0098)
R Manual	-0.0019 (0.0056)	-0.0029 (0.0073)	-0.0041 (0.0065)	-0.0041 (0.0061)	-0.0012 (0.0084)	-0.0063 (0.0073)	0.0052 (0.0078)	0.0072 (0.0100)	0.0064 (0.0106)
NR Manual Physical	0.0013 (0.0057)	0.0010 (0.0074)	0.0009 (0.0065)	-0.0013 (0.0073)	-0.0155 (0.0099)	0.0097 (0.0087)	-0.0097 (0.0073)	-0.0094 (0.0096)	-0.0159* (0.0093)
Social Skill	0.0050 (0.0067)	-0.0040 (0.0100)	0.0104 (0.0092)	0.0097 (0.0100)	0.0012 (0.0164)	0.0063 (0.0083)	-0.0030 (0.0098)	-0.0049 (0.0162)	-0.0037 (0.0142)
Observations	19,316	9,586	9,730	10,243	4,971	5,272	6,763	3,356	3,407

Notes: The table presents the probability of holding multiple jobs associated with the task intensity measures by race. The dependent variable is equal to one if that an individual is holding multiple jobs, giving the coefficient estimates a percentage point interpretation. Demographic controls are included in all specifications. The computed standard errors are robust to clustering on individuals and are presented in parentheses. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

6. Conclusion

A large literature documents the relationship between occupational task intensity and labor market outcomes (e.g., Autor, Levy, and Murnane 2003; Autor and Dorn 2013; Deming 2017), variables which are closely associated with well-being in retirement. However, the distribution of labor market tasks by age and other demographics has received less attention (Hurst, Rubinstein, and Shimizu 2021). With the exception of Hudomiet and Willis (2021), who focus on computerization of occupations, to our knowledge, there has been no study focused specifically on the allocation of tasks for specific age groups. Filling this void in our understanding of how work changes for people as they age will be particularly important for SSA policy.

In this paper, we examine the relationship between the evolution of tasks and corresponding labor market outcomes on workers of different ages. By combining task data from O*NET and ORS and survey data from NLSY79 and ACS, we describe how the labor market has developed over the last two decades for different age groups. We find substantial heterogeneity in the distribution of cognitive, social, and physical tasks across age groups in the ACS. Results from the NLSY79 show that as workers age they become more sensitive to changes to task intensity.

Stark racial divides in the age-specific allocation of tasks offer a common theme from our results. As they age, White men work in the most cognitively demanding jobs, while White women work in the least physically demanding occupations. Black and Hispanic men maintain the highest physical task intensity as they age, whereas White men transition to more cognitively intensive work early in their careers and remain in jobs with similar cognitively intensive work until late career.

SSA policy makers will soon be challenged by financial stress on the federal government's entitlement programs, largely due to the exit of baby boomers from the labor force. The relationship between work tasks and relevant employment outcomes, such as earnings and labor force participation, will play an important role in determining the effects of the coming SSA reforms. Because Black and Hispanic retirees rely more on Social Security payments, which also depend on length of work life and career earnings, adjustments to retirement age and benefits will likely have disproportionate effects on these groups.

We also believe there is much to be learned from future research on work tasks and retirement-related outcomes. For example, with the data used for this study, it is possible to examine the relationship between occupational task intensity and early retirement. The correspondence of work tasks with disability status and the uptake of disability benefits, prior to full-retirement age, is also an important area of future study.

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Table 5.1A – Impact of Control Variables on Hourly Wage Rates

Control Variable	All		50 and Older		Younger than 50	
	(2)	(3)	(5)	(6)	(8)	(9)
Female	-0.4104*** (0.0187)	-0.3705*** (0.0204)	-0.3960*** (0.0232)	-0.3511*** (0.0250)	-0.4189*** (0.0211)	-0.3853*** (0.0231)
Hispanic	-0.0070 (0.0215)	0.0609** (0.0246)	0.0118 (0.0267)	0.0857*** (0.0299)	-0.0252 (0.0246)	0.0341 (0.0283)
Black	-0.0867*** (0.0194)	-0.0176 (0.0235)	-0.0897*** (0.0239)	-0.0112 (0.0289)	-0.0822*** (0.0220)	-0.0232 (0.0264)
Married	0.2339*** (0.0251)	0.2162*** (0.0269)	0.2382*** (0.0337)	0.2322*** (0.0361)	0.2330*** (0.0273)	0.2050*** (0.0293)
Separated	0.0561 (0.0388)	0.0588 (0.0419)	0.0552 (0.0534)	0.0650 (0.0556)	0.0652 (0.0451)	0.0576 (0.0504)
Divorced	0.1208*** (0.0276)	0.1209*** (0.0297)	0.1422*** (0.0362)	0.1456*** (0.0388)	0.1032*** (0.0310)	0.1002*** (0.0336)
Widowed	-0.0229 (0.0594)	0.0050 (0.0598)	0.0018 (0.0632)	0.0515 (0.0634)	-0.0752 (0.1001)	-0.0942 (0.1095)
High School Graduate	0.2341*** (0.0306)	0.1879*** (0.0349)	0.2450*** (0.0429)	0.1981*** (0.0476)	0.2243*** (0.0344)	0.1780*** (0.0405)
Some College	0.3485*** (0.0331)	0.2381*** (0.0388)	0.3346*** (0.0450)	0.2269*** (0.0512)	0.3583*** (0.0377)	0.2477*** (0.0452)
College Graduate	0.6548*** (0.0363)	0.4998*** (0.0432)	0.6091*** (0.0489)	0.4580*** (0.0565)	0.6991*** (0.0411)	0.5434*** (0.0498)
Age	0.0044 (0.0035)	0.0013 (0.0039)	-0.0016 (0.0045)	-0.0046 (0.0049)	0.0080* (0.0042)	0.0051 (0.0046)
Very Good		-0.0473** (0.0191)		-0.0514** (0.0232)		-0.0469** (0.0221)
Good		-0.0746*** (0.0253)		-0.1242*** (0.0317)		-0.0238 (0.0275)
Fair		-0.1453*** (0.0471)		-0.1056* (0.0561)		-0.1822*** (0.0607)
Poor		0.0130 (0.0905)		-0.0008 (0.1203)		0.0484 (0.1039)
Rotter Score (1979)		-0.0146*** (0.0036)		-0.0133*** (0.0045)		-0.0154*** (0.0040)
Rotter Score (2014+)		-0.0431*** (0.0039)		-0.0431*** (0.0049)		-0.0430*** (0.0044)
AFQT (1981)		0.0025*** (0.0004)		0.0026*** (0.0005)		0.0022*** (0.0005)
Constant	8.0804*** (0.2139)	8.7695*** (0.2349)	8.1880*** (0.2830)	8.8372*** (0.3113)	7.9812*** (0.2602)	8.7632*** (0.2757)
Control Variables:						
Year	Yes	Yes	No	No	Yes	Yes
Region	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Observations	36,322	30,412	17,913	15,434	18,409	14,978

Notes: The table presents the earnings returns/penalties associated with the task intensity measures. The dependent variable is the natural logarithm of the inflation-adjusted hourly wage rate (in 2018 dollars), giving the coefficient estimates a percentage change interpretation. The computed standard errors are robust to clustering on individuals and are presented in parentheses. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.