**Online Appendix for "Task-Based Discrimination"**
**by Erik Hurst, Yona Rubinstein, and Kazuatsu Shimizu**

# Appendix A Data Description

In our empirical work, we primarily use data from three sources: cross-sectional labor market data from the Census/ACS, occupational task measures from DOT and O*Net, and panel micro data from the NLSY79 and NLSY97 that contain measures of worker pre-labor market skills.

## Appendix A.1 Census/ACS Sample

To access the Census/ACS data, we download the micro data directly from the IPUMS USA website (Ruggles et al. (2021)). We use data from the 1960, 1970, 1980, 1990, and 2000 US Censuses. Additionally, we pool together data from the 2010-2012 and the 2016-2018 American Community Surveys. We refer to the former as the 2012 ACS sample and the latter as the 2018 ACS. We restrict our Census and ACS samples to those between the ages of 25 and 54 (inclusive), those who report their race as "White" ($race = 1$) or "Black" ($race = 2$), and those born within the United States ($bpl \leq 56$). We exclude from our sample anyone who is living in group quarters (keep $gq = 1$), anyone who reports being Hispanic (keep $hispan = 0$) and those who are self-employed (keep $classwkr = 2$). Finally, we exclude any employed worker whose occupation has missing task values. This last restriction reduces the overall sample by less than one percent.

## Appendix A.2 NLSY Data

We also use data from the 1979 and the 1997 National Longitudinal Survey of Youth, NLSY79 and NLSY97, respectively. The NLSY79 is a representative survey of 12,686 individuals who were 15-22 years old when they were first surveyed in 1979. Individuals were interviewed annually through 1994 and biennially since then. The NLSY97, which follows a nearly identical structure to the NLSY79, is a nationally representative panel survey of 8,984 individuals who were 12-16 years old when they were first surveyed in 1997. Individuals were interviewed annually through 2011 and biennially since then.

The NLSY79 and the NLSY97 waves provide detailed demographic information, such as age, gender, race, and educational attainment. We restrict our primary sample to Black and White men only. We exclude observations with missing demographics or missing measures of cognitive, non-cognitive, or social skills. Our wage and employment sample focuses on prime-aged male who are full-time and full-year workers. We exclude observations that report less than 1,750 annual worked hours or hourly wages lower than 2 or higher than 500 in 2010 CPI prices. We further exclude observations with missing occupation codes. When comparing over time and across cohorts of birth, we restrict the NLSY79 sample to individuals aged 25-37 for comparability to the NLSY97 wave.

## Appendix A.3 Task Measures Creation

To assess the extent to which Black and White workers sort into different occupations, perform different tasks and consequently earn different amounts, we use data from the following to measure the skills demanded in each occupation: (i) the U.S. Department of Labor's Dictionary of Occupational Titles (DOT) and (ii) the Occupational Information Network (O*NET) sponsored by the U.S. Department of Labor/Employment and Training Administration (USDOL/ETA). The DOT was constructed in 1939 to help employment offices match job seekers with job openings. It provides information on the skills demanded of over 12,000 occupations. The DOT was updated in 1949, 1964, 1977, and 1991, and replaced by the O*NET in 1998.

The DOT and the O*NET measure task requirements associated with many detailed occupations. For example, one O*Net question asks whether the occupation requires dealing with external customers; survey respondents provide responses on an ordinal scale of 0 to 5 where the higher values signify that the job requires more of that task. Different questions have answers that range on different ordinal scales (e.g., 0-5, 1-7, 0-10, etc.). We again downloaded the tasks measures directly from the replication package for Deming (2017b).[A1] For all questions we use from both surveys, we follow Deming (2017b) and re-scale the answers so they range from zero to ten to ensure consistency in units when we combine questions. We convert the answers into z-score units after combining them into different tasks.

We focus on four occupational task measures that are relevant for our study: (i) *Abstract*; (ii) *Routine*; (iii) *Manual* and (iv) *Contact*. The first three measures were created following the definitions in Autor and Dorn (2013) using the DOT data while the last measure builds on Deming (2017b) using the O*Net data. Our goal is to stay as close to possible to the definitions of task measures developed by others to focus our analysis on the racial differences in these measures. Throughout the main paper, we define the key task measures as follows:

***Abstract***: indicates the degree to which the occupation demands (i) analytical flexibility, creativity, reasoning, and generalized problem-solving, and (ii) complex interpersonal communications such as persuading, selling, and managing others. Following Dorn (2009) and Autor and Dorn (2013), we measure *Abstract* tasks in practice by using the 1977 DOT data using the average scores from questions measuring *General Educational Development in Math (GED-Math)* and *Direction, Control, and Planning of Activities (DCP)*. Higher levels of *GED-Math* are associated with higher quantitative *Abstract* tasks. Occupations with high measures of *GED Math* include various medical professionals, various engineers, accountants, and software developers. Higher levels of *DCP* are associated with higher levels of abstract thinking associated with management, organizational, and teaching tasks. Occupations with high measures of *DCP* include various managers, high school teachers, college professors and judges. To create our measure of the *Abstract* task content of an occupation, we follow Autor and Dorn (2013) and Deming (2017b) and take the simple average of *GED-Math* and *DCP* for each occupation.

***Routine***: measures the degree to which the task requires the precise attainment of set standards and/or repetitive manual tasks. Following Dorn (2009) and Autor and Dorn (2013), we measure *Routine* task using the 1977 DOT data taking the average scores from questions measuring *Finger Dexterity (FINGDEX)* and *Set Limits, Tolerances, or Standards (STS)*. *FINGDEX* measures the ability to move fingers and manipulate small objects with fingers

[A1] See Deming (2017a) for the link to the Deming's replication package.

and serves as a proxy for repetitive routine manual tasks. Occupations with high measures of *FINGDEX* include secretaries, dental hygienists, bank tellers, machinists, textile sewing machine operators, dressmakers, and x-ray technology specialists. *STS* measures the adaptability to work situations requiring setting of limits and measurements and serves as a proxy for routine cognitive tasks. Occupations with high measures of *STS* include meter readers, pilots, drafters, auto mechanics, and various manufacturing occupations. To create our measure of the *Routine* task content of an occupation, we follow Autor and Dorn (2013) and Deming (2017b) and take the simple average of *FINGDEX* and *STS* for each occupation.

***Manual***: measures the degree to which the task demands eye, hand, and foot coordination. Following Dorn (2009), Autor and Dorn (2013) and and Deming (2017b), we measure *Manual* using the 1977 DOT data using the question *EYEHAND* which measures the ability to coordinately move hand and foot in accordance with visual stimuli. Occupations with high measures of *EYEHAND* include athletes, police and fire fighters, drivers (taxi, bus, truck), skilled construction (e.g, electricians, painters, carpenters) and landscapers/groundskeepers. To create our measure of the *Manual* task content of an occupation, we just use the *EYEHAND* measure for that occupation.

***Contact***: measures the extent that the job requires the worker to interact and communicate with others whether (i) within the organization or (ii) with external customers/clients or potential customers/clients. For this measure of *Contact* tasks we use two 1998 O*NET work activity variables taken from Deming (2017b). Specifically, we use the variables *Job-Required Social Interaction (Interact)* and *Deal With External Customers (Customer)*. *Interact* measures how much workers are required to be in contact with others in order to perform the job. *Customer* measures how much workers have to deal with either external customers (e.g., retail sales) or the public in general (e.g., police work). To make our measure of the *Contact* task content of an occupation, we take the simple average of *Interact* and *Customer* for each occupation. Occupations with high measures of *Contact* tasks include various health care workers, waiter/waitress, sales clerks, lawyers, various teachers, and various managers.

The data we use from Deming (2017b) are available at the 3-digit occupational code level. We use Deming (2017b)'s crosswalk to merge these measures to (i) the Census and the American Community Surveys (ACS) and (ii) the National Longitudinal Survey of the Youth (NLSY 1979 and 1997 waves) which we use for our analysis. Again, we download these data directly from Deming's replication file at `https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/CYPKZH`.[A2]

## Appendix A.4 Task Composition of Selected Occupations

Appendix Table R1 shows the *Abstract*, *Contact*, *Routine* and *Manual* task composition of a selected set of occupations. As seen from the table, some occupations have high task contents of both *Abstract* and *Contact* tasks (e.g., lawyers) while others have relatively low *Abstract* task content but relatively high *Contact* task content (e.g., retail sales clerks). Likewise, some occupations have relatively high contents of all four task measures (e.g., physicians) while others have relatively low contents of all four task measures (e.g., mail carriers).

[A2]As we discuss in the data replication README file, we slightly adjust Deming's crosswalk to consistently merge the task measures into our Census/ACS sample given our analysis starts in 1960 which is earlier than when Deming's analysis starts.

Table R1: Task Content of Selected Occupations

| Occupation | *Abstract* | *Contact* | *Routine* | *Manual* |
|---|---|---|---|---|
| Automobile mechanics | -0.39 | -0.38 | 1.21 | 0.73 |
| Carpenters | -0.27 | -0.87 | 1.26 | 2.23 |
| Chief executives and public admin | 1.16 | 1.25 | -1.18 | -0.52 |
| Civil engineers | 2.30 | 0.09 | 1.22 | 0.59 |
| Clergy and religious workers | 0.05 | 0.96 | -1.47 | -0.90 |
| Computer scientists | 1.07 | 0.14 | -0.76 | 0.03 |
| Financial managers | 1.99 | 0.50 | -1.10 | -0.89 |
| Gardeners and groundskeepers | 0.42 | -0.50 | -0.82 | 0.86 |
| Janitors | -0.82 | -0.52 | -0.33 | 0.70 |
| Lawyers | 1.11 | 1.01 | -1.67 | -0.89 |
| Machine operators, n.e.c. | -0.82 | -1.22 | 0.47 | 0.04 |
| Mail carriers for postal service | -0.80 | 0.01 | -1.48 | -0.72 |
| Nursing aides, orderlies, and attendants | -0.37 | 0.95 | -0.48 | 0.15 |
| Physicians | 2.17 | 1.15 | 0.05 | 0.29 |
| Police, detectives, and private investigation | -0.55 | 0.86 | -1.47 | 1.62 |
| Primary school teachers | -0.14 | 0.76 | -1.44 | 0.65 |
| Retail sales clerks | -0.63 | 1.71 | -0.84 | -0.69 |
| Secretaries | -0.39 | 0.80 | 1.76 | -0.90 |
| Social workers | 1.66 | 1.53 | -1.41 | -0.85 |
| Truck, delivery, and tractor drivers | -0.87 | 0.58 | -1.37 | 1.98 |
| Waiter/waitress | -0.78 | 1.51 | -1.43 | 0.66 |

*Notes:* Table shows the task content (in z-score units) of various occupations.

## Appendix A.5 Persistence of Task Composition of Occupations Over Time

In the main paper, we follow the bulk of the literature by imposing that the task content of occupations are constant over time. However, we have performed a battery of robustness exercises to explore the sensitivity of our results to holding the task composition of occupations constant over time. As we discuss in the main text, our key results are not sensitive to our choice to hold the task content of occupations constant over time. There are two reasons for this. First, as we show below, the task content of occupations – expressed in z-score units – are quite persistent over time. Second, to the extent that the task content of occupations changes over time, they do not change in a way that alters our estimates of the racial task gaps.

Table R2 highlights the persistence in the task composition of occupations over time. As noted in the main text, we create measures of *Abstract*, *Routine*, and *Manual* tasks associated with each occupation using the 1977 DOT data, while we create measures of the *Contact* task content of each occupation using the 1998 O*Net data. Panel A reports the bi-variate regression coefficients and the corresponding correlations between 1977 and 1991 DOT occu-

Table R2: Persistence of Occupational Task Content Over Time

| Panel A: 1977 DOT vs. 1991 DOT | | |
|---|---|---|
| | Coefficient (S.E.) | Correlation |
| *GED-Math* | 1.00 (0.01) | 0.99 |
| *DCP* | 0.92 (0.02) | 0.95 |
| *FINGDEX* | 0.94 (0.02) | 0.95 |
| *STS* | 0.93 (0.02) | 0.92 |
| *EYEHAND* | 0.96 (0.01) | 0.96 |
| **Panel B: 1998 O*NET vs. 2021 O*NET** | | |
| | Coefficient (S.E.) | Correlation |
| *Math* | 1.01 (0.02) | 0.85 |
| *Contact* | 0.96 (0.03) | 0.70 |

*Notes:* Panel A shows the results of a set of bi-variate regressions of the task content of an occupation as measured in the 1977 DOT on the task content of that same occupation as measured in the 1991 DOT. The panel reports the regression coefficient on the 1991 DOT occupational task measure (column 1) as well as the correlation (column 2). Each regression in the panel has 485 occupations. Panel B shows the results of a regression of the task content of an occupation as measured in the 1998 O*NET data on the task content of that same occupation as measured in the 2021 O*NET. *Contact* tasks are measured as the sum of *Interact* and *Customer* (as in the main text). *Math* tasks are measured similarly as in Deming (2017b). Each regression in this panel has 799 occupations. Otherwise the structure of the results in this panel is symmetric to what is shown in Panel A. Standard errors in parentheses.

pational task contents for all the five underlying task measures that comprise the *Abstract*, *Routine* and *Manual* task measures, which are summarized in Autor et al. (2003).[A3] The task measures exhibit extremely high persistence; the regression coefficients between the 1977 and the 1991 measures of *GED-Math*, *DCP*, *FINGDEX*, *STS*, and *EYEHAND* range from 0.92 to 1 and the correlations range from 0.92 to 0.99. In Panel B, we document the persistence for both our *Contact* task measure and for an alternate measure of *Abstract* tasks – the *Math* task content of an occupation – using data from the 1998 and 2021 O*Net data.[A4] Following

[A3] We downloaded the DOT data from different years directly from David Autor's website. See Autor (2024).
[A4] The files are downloaded directly from the O*NET Resource Center website at www.onetcenter.org (U.S.

Deming (2017b), we define the *Math* task measure by combining O*Net questions measuring (i) the extent to which an occupation requires mathematical reasoning, (ii) whether the occupation requires using mathematics to solve problems, and (iii) whether the occupation requires knowledge of mathematics. Like with the DOT data between the 1977 to 1991 period, the regression coefficients are statistically indistinguishable from 1 although the correlations are somewhat lower, reflecting the greater desegregation into 799 occupations in the O*NET data compared to 485 using the DOT.

At first blush, these patterns may seem at odds with recent research by Atalay et al. (2020) and Cavounidis et al. (2021) showing that the task content of occupations has changed sharply over time. However, that is not the case. The difference in conclusions stems from the fact that we are measuring the task content of an occupation in z-score units. We normalize the mean of our task measures to zero in each year and thereby only explore *relative* variation in the task measures across occupations, which is highly persistent over time. On the other hand, Atalay et al. (2020) and Cavounidis et al. (2021) highlight that over time, most occupations are requiring more *Abstract* tasks and less *Routine* tasks in *absolute* terms; this within-occupation shift is large relative to the change in aggregate task composition of the economy resulting from workers migrating to occupations that require more *Abstract* and less *Routine* tasks (i.e., cross-occupation sorting). By expressing task contents in z-score units, those systematic shifts in the aggregate task content of jobs are removed from our task measures. Instead, for us, the extent to which those aggregate shifts occur, they will be absorbed into our model estimated $\beta_{kt}$'s. In fact, this is exactly the type of shift we are trying to identify in the quantitative analysis we perform in our model.

# Appendix B Robustness of Racial Task Gaps: Alternate Specifications

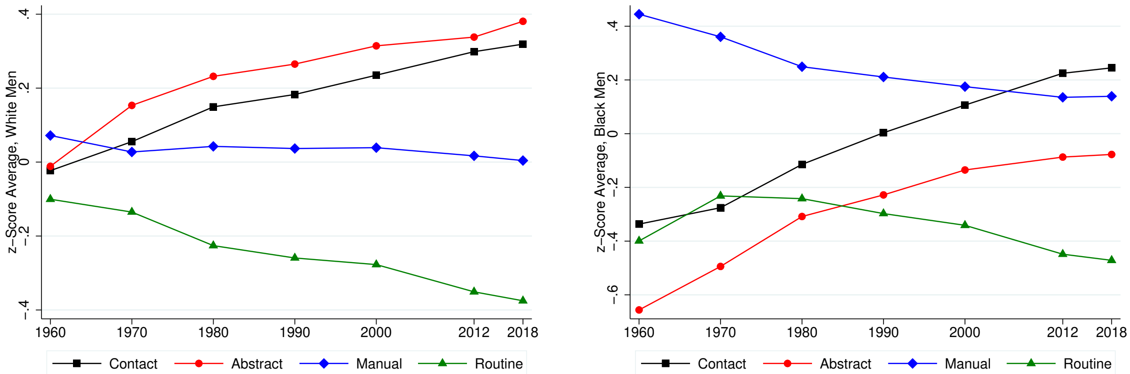
In this section of the appendix, we show the robustness of our results with respect to the time series trends in racial task gaps. We start by showing the raw task trends separately for Black and White men (in the main text, we only show the racial gaps). We then show the robustness of the racial task gaps separately for different education groups and birth cohorts. We conclude by showing the trends in racial task gaps using 66 broad occupation categories as opposed to using the over 300 narrow occupation categories.

## Appendix B.1 Raw Occupational Task Sorting, By Race

Appendix Figure R1 plots the raw trends in occupational tasks separately for White (Panel A) and Black (Panel B) men since 1960 using the Census/ACS data. As in the main text, we restrict our sample to native born men between the ages of 25 and 54 who are not self employed and who report currently working full time (e.g., at least 30 hours per week). Specifically, Appendix Figure R1 reports the coefficients on the year dummies ($\xi^g_{kt}$) from the following

Department of Labor, Employment and Training Administration, 2023).

Figure R1: Raw Task Trends: White and Black Men




Panel A: White Men    Panel B: Black Men

*Notes:* Figure shows the raw trend in the task content of jobs for White and Black men using Census and ACS data. Sample restricted to native born individuals between the ages of 25 and 54 who are not self-employed but who are working full time. Tasks are expressed as z-scores across occupations. Task-specific regressions are run separately for White men (Panel A) and Black men (Panel B) and were weighted using Census/ACS individual sampling weights.

regressions using our individual Census/ACS data:

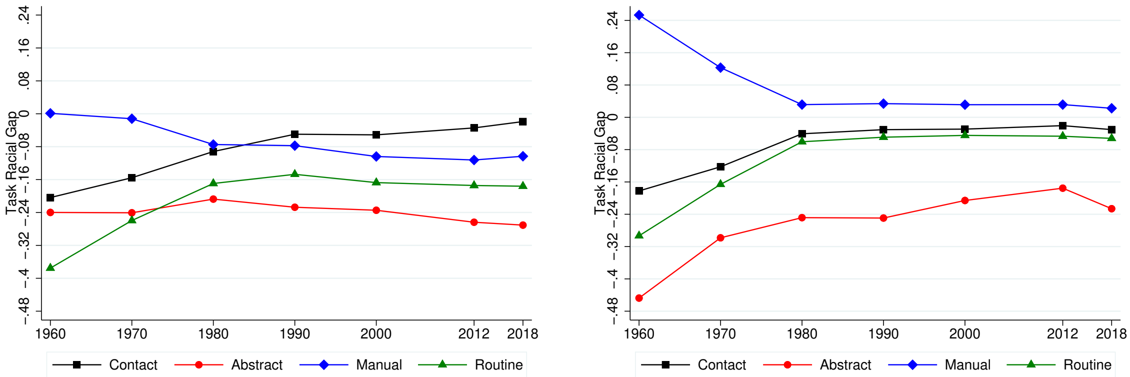
$$\tau^k_{iogt} = \sum_t \xi^g_{kt} D_t + \epsilon_{iogt} \quad \text{(R1)}$$

where, as in the main text, $\tau^k_{iogt}$ is the task content of task $k$ for individual $i$ from group $g$ working in occupation $o$ in period $t$. Task contents are expressed in z-score units. We run this regression separately for each of our two groups $g$ – White men and Black men – and for each of our four task measures. As a result, all coefficients are indexed by $g$ and $k$. $D_t$ is a vector of dummies that take the value of 1 if the year is, respectively, 1960, 1970, 1980, 1990, 2000, 2012, or 2018. The coefficient on the year dummies from these regressions, $\xi^g_t$ are plotted in the figure.

## Appendix B.2 Racial Task Gaps, by Education Levels

We next show robustness of the time series patterns in racial task gaps within different education groups using our main specification described in the text. Panel A of Appendix Figure R2 redoes the main results of Figure 1 of the main text (with demographic controls) but segmenting the sample to only those individuals with education less than a bachelor's degree. Panel B shows the same specification but restricting the sample to those individuals with a bachelors degree or more. These figures show that our time series patterns of the changing racial task gaps that we highlight in the main paper are found in both higher and lower education samples. For both education groups, there was a convergence in *Contact* tasks and a relatively constant trend in *Abstract* tasks; for the higher educated individuals, the racial gap in *Abstract* tasks is relatively constant from 1970 onward.

Figure R2: Race Gap in Tasks: By Educated Groups




PANEL A:
LESS THAN A BACHELORS DEGREE

PANEL B:
BACHELORS DEGREE OF MORE

*Notes:* Figure re-estimates Panel B of Figure 1 of the main text separately for those with less than a bachelors degree (Panel A) and those with a bachelors degree or more (Panel B).

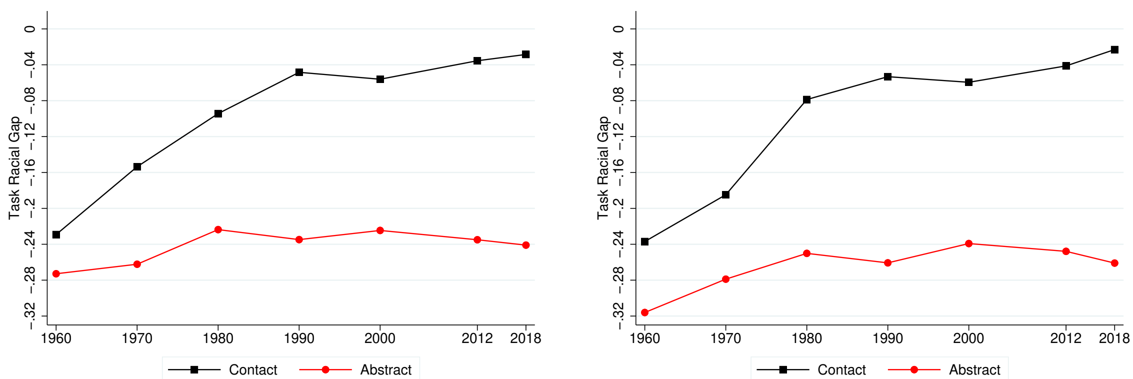
## Appendix B.3 Racial Task Gaps, Excluding Low Wage Workers and Excluding Highly Unionized Industries

As discussed in the main text, the literature has shown that changes in the minimum wage and changes in unionization rates can change the racial wage gap. These forces within our model are captured within the term $A_t^b$. However, it could be argued that these forces can also cause differential task returns given that unionization rates tend to be high in industries with certain task requirements and that industries more like to be bound by the minimum wage (e.g., restaurant workers) also are more likely to require certain tasks.

To see if changes in the minimum wage can be driving the time series trends in the racial gap in the task content of occupations we exclude all workers in the bottom 10% of the wage distribution and re-estimate our key descriptive results in Panel B of Figure 1. By excluding low wage workers, we are excluding those workers who may be directly effected by a binding minimum wage. In particular, we take our main sample of prime age Black and White individuals and compute the wage distribution within each year for this sample. We then exclude those in the bottom 10% of the distribution and re-estimate equation (8). The results are shown in Panel A of Appendix Figure R3. As seen from Panel A, the time series trends in the racial gap in *Contact* tasks (black line, with squares) and the racial gap in *Abstract* tasks (red line, with cirles) are nearly identical to what we find in Figure 1 of the main text. It does not appear that changes in the minimum wage is the primary factor explaining why the racial gap in *Contact* tasks narrowed substantially but the racial gap in *Abstract* tasks remained persistently large.

Panel B of Appendix Figure R3 shows are main descriptive patterns excluding workers in highly unionized sectors. In particular, we recompute our key findings on the time series trends in racial task gaps excluding workers from the Construction, Manufacturing, Utilities, and Public industries. These are the industries with the highest unionization rates for men. As seen from the figure, our key descriptive findings are nearly identical when we exclude the unionized sectors. Going back to the introduction of the paper, we describe how the racial gap in occupational sorting into Sales occupations has narrowed substantially over time while racial gap in Engineering occupations remained large. These findings are underlying the patterns in Panel B; neither of these occupations are highly unionized.

Figure R3: Race Gap in Tasks: Excluding Low Wage Workers and Those in Highly Unionized Sectors




Panel A: Exclude Low Wage Workers

Panel B: Exclude Those in Unionized Sectors

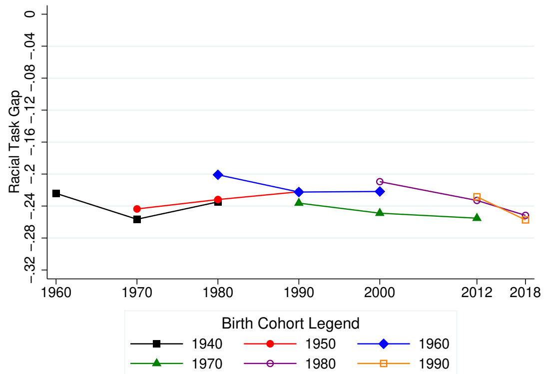
*Notes:* Figure re-estimates Panel B of Figure 1 of the main text separately exclusing those in the bottom 10 percent of the wage distribution (Panel A) and excluding those working in highly unionized sectors (Panel B). We classify the highly unionized sectors as those workers whose industry is Construction, Manufacturing, Utilities, or the Public Sector.

Collectively, the results in Figure R3 provide supporting evidence that changes in minimum wage laws or changes in unionization rates are unlikely to be the primary forces driving the racial convergence with respect to sorting into occupations requiring *Contact* tasks or the stagnation in the racial convergence with respect to sorting into occupations requiring *Abstract* tasks.

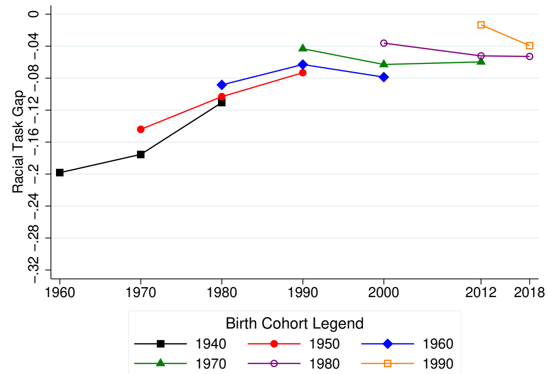
## Appendix B.4 Racial Gap in Task Measures, By Birth Cohort

Our model of occupational choice is static. In Figure R4, we re-estimate equation (8) separately for various 10-year birth-cohorts in each of the sample years. This allows us to examine how the racial task gaps evolve both within and across the various birth cohorts. The figure shows the results for *Abstract* (Panel A) and *Contact* (Panel B) tasks. As seen from the figure, most of the changes in the racial task gaps – to the extent they happen – occur across birth cohorts. Given this, we are comfortable omitting life-cycle forces within our model.

Figure R4: Racial Differences in the *Abstract* and Contact Tasks, By Birth Cohort




Panel A: *Abstract* Task



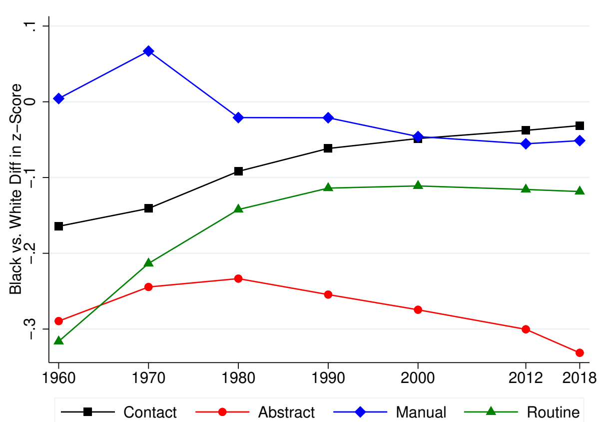

Panel B: Contact Task

*Notes:* Figure shows the estimated $\lambda_t^k$'s from the regression specified in equation (8) separately for each 10 year birth-cohort. For example, the 1940 cohort is defined as those individuals born between 1935 and 1944. Aside from the cohort nature of this exercise, the sample and specification are the same as in Panel B of Figure 1. The results for *Abstract* tasks are shown in Panel A while the results for *Contact* tasks are shown in Panel B.

## Appendix B.5 Racial Task Gaps Using Broader Occupation Codes

In our main empirical work, we use the over 300 detailed occupation codes provided by the Census. It is at these detailed occupation codes that Autor and Dorn (2013) and Deming (2017b) provide measures of occupational task requirements. However, for our model estimation, we perform our analysis at 66 broader occupation categories instead of the over 300 detailed occupation categories.

Figure R5: Race Gap in Task Measures, Broad Occupational Definitions




*Notes:* Figure re-estimates Panel B of Figure 1 of the main text using 66 broad occupational task measures (instead of over 300 detailed occupational task measures). The sample and specification is otherwise the same as in Panel B of Figure 1 of the main text.

In this subsection of the Robustness Appendix, we show that the racial task gaps using the 66 broader occupation categories are nearly identical to the racial task gap using the more detailed occupation codes. In particular, we aggregate the Census detailed occupation codes to the 66 occupation codes used in the main analysis of Hsieh et al. (2019). These 66 broad occupation codes come from the 1990 Census Occupation Code sub-categories and include categories like "Executive, Administrative, and Managerial", "Engineers", "Math and Computer Science", "Health Diagnosing", "Teachers, Postsecondary", "Teachers, Non-Postsecondary", "Sales", "Food Prep and Service", "Precision Production Supervisor", etc.[A5] Each of the detailed occupation codes maps to exactly one of the broad occupation codes. For example, all the various detailed engineering occupations are mapped to the broad "Engineers" occupational category. To make the task requirements for the broad occupation categories we take the weighted average of the task measures for each of the corresponding detailed occupations. For all years, we use the 1980 occupational shares of white men as the weights to aggregate the detailed occupational task measures into the broader occupational task measures.

The results of the racial task gaps using our broad occupational classification are shown in Figure R5. The results in this figure come from the same specification and sample as shown in Panel B of Figure 1 of the main text. The only difference is that task measures are defined at the broad occupation level as opposed to the detailed occupation level. As seen from this figure, the racial task trends are nearly identical to what are shown in Figure 1 of the main text. In particular, there was substantial convergence in the racial gap in *Contact* tasks and no convergence in the racial gap in *Abstract* tasks.

# Appendix C Robustness of Racial Task Gaps: Alternate Task Definitions

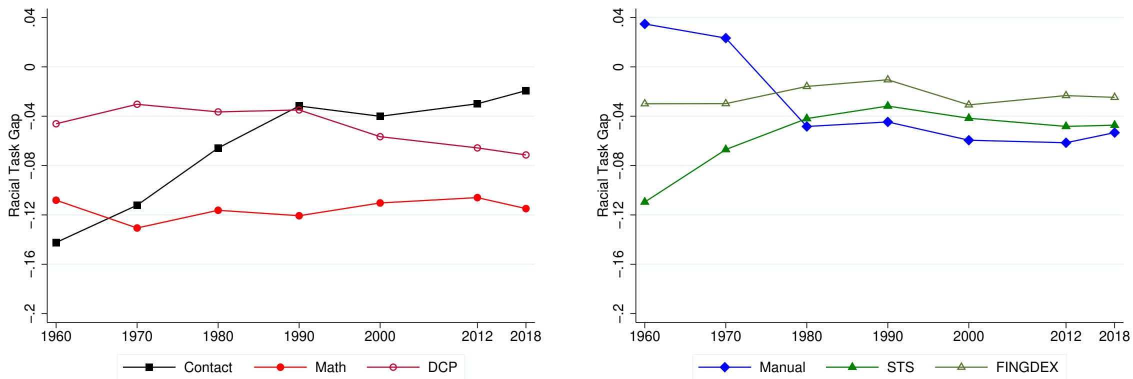
In this section of the appendix, we explore the robustness of our results to alternate definitions for our four task measures. We begin by disaggregating our current task measures into their separate task components. We then explore the racial gaps in alternate definitions of our four main task categories. As seen in this section, our results are quite robust to alternate task definitions.

## Appendix C.1 Decomposing Task Measures into Sub-Components

Within the main paper, we used three task measures emphasized in the recent literature using DOT data: *Abstract*, *Routine* and *Manual* tasks. As discussed above, these three measures of tasks were created using five separate questions from the DOT data. *Abstract* task is a combination of $GED - Math$ and $DCP$. *Routine* task is a combination of $FINGDEX$ and $STS$. In this subsection of the appendix, we move from using four tasks measures (*Abstract*, *Routine*, *Manual*, and *Contact*) to six tasks measures (*GED-Math*, *DCP*, *FINGDEX*, *STS*, *Manual* and *Contact*). In particular, we re-estimate the results in Panel B of Figure 1 using six task measures instead of four. The sample used is the same as in Panel B of Figure 1 of the main text. Moreover, like with our main descriptive analysis in Section 3 of the main

[A5] For a full list of the 66 Broad Occupational Categories, see https://usa.ipums.org/usa/volii/occ1990.shtml.

Figure R6: Race Gap in Tasks: Disaggregated Task Measures




Panel A Panel B

*Notes:* Figure re-estimates Panel B of Figure 1 of the main text with six task components instead of four. In particular, we disaggregate *Abstract* tasks into its (1) *Math* and (2) DCP sub-components. Likewise, we disaggregate *Routine* tasks into its (1) STS and (2) Finger subcomponents. The sample is the same as in Panel B of Figure 1 of the main text. We display the results over two panels for readability.

paper, we use our 3000 detailed occupations for this analysis.[A6] The race coefficients from these yearly regressions are plotted in Appendix Figure R6. We plot the coefficients in two panels instead of one for readability.

The figure shows that the main take-aways highlighted in the text are unaltered when using the six task measures. Specifically, there have been no relative gains by Blacks with respect to either component of *Abstract* tasks; Blacks were underrepresented in both *GED Math* and *DCP* in 1960 and the race gap was roughly constant through 2018. However, Blacks made large gains in *Contact* tasks over this time period.

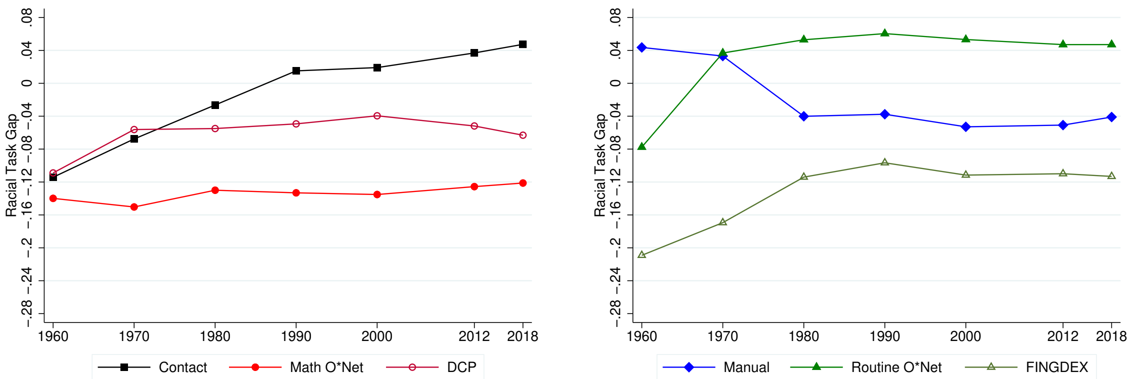
## Appendix C.2 Robustness to O*Net Measures of *Math* and *Routine* Tasks

Deming (2017b) used data from 1998 O*Net survey to make two alternate measures of *Math* and *Routine* occupations. For his alternate *Math* task measure, he combines O*Net questions measuring (i) the extent to which an occupation requires mathematical reasoning, (ii) whether the occupation requires using mathematics to solve problems, and (iii) whether the occupation requires knowledge of mathematics. The measure of the *GED-Math* task content of an occupation created using DOT data is highly correlated with Deming's *Math* task content of an occupation created using the O*Net data; the correlation between the two series (weighted by 1990 population in each occupation) is 0.81.

For his alternate *Routine* task measure, Deming again uses the 1998 O*Net and combines the questions measuring (i) how automated is the job and (ii) how important is repeating the same physical activity (e.g. key entry) or mental activities (e.g., checking entries in a ledger

[A6] We will use the detailed occupation codes for all results in this section of the appendix.

Figure R7: Race Gap in Tasks: Alternate Measures of *Routine* and *Math* Task Measures




Panel A Panel B

*Notes:* Figure re-estimates Panel B of Figure 1 of the main text with six task components instead of four. In particular, we disaggregate *Abstract* tasks into its (1) *Math* and (2) *DCP* sub-components. For this figure, we use Deming's measure of occupational *Math* task measures using the O*Net data. Likewise, we disaggregate the DOT *Routine* tasks into its (1) *STS* and (2) *Finger* subcomponents. However, we replace the DOT *STS* measure with Deming's *Routine* task measure using O*Net data. The sample is the same as in Panel B of Figure 1 of the main text. We display the results over two panels for readability.

over and over, without stopping to perform the job). This measure is highly correlated with the *STS* portion of *Routine* tasks within the DOT data. However, conditional on controlling for the *STS* content of a job, the Deming *Routine* task measure using the O*Net data is uncorrelated with the occupations *FINGDEX* task content.[A7] Given this, we treat Deming's *Routine* task measure created using the 1998 O*Net data as being an alternative for the *STS* task measure within the DOT data.

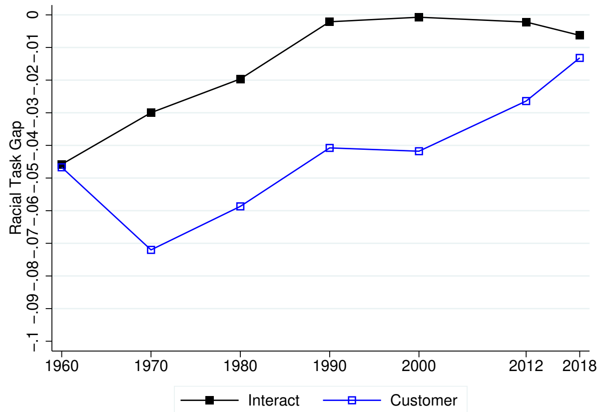
With this in mind, we explore the sensitivity of our results to using Deming's *Math* and *Routine* measure using the O*Net data as alternative task measures for the *GED-Math* and *STS* measures using the DOT data. We re-estimate the patterns in Appendix Figure R6 with the six task measures but we use the alternate Deming measures for *Math* and *STS*. The results of this regression are shown in Appendix Figure R7. Again, we display the results over two panels for readability. Our main results are unchanged with these two alternative task measures. Primarily, there has still been no racial progress in the *Math* task content of an occupation over the last 60 years. However, there have been a large convergence in the racial gap in occupational *Contact* tasks.

## Appendix C.3 Alternate Measures of *Contact* Tasks

One of the key findings in our paper is the comparison of the racial convergence in *Contact* tasks relative to *Abstract* tasks in the U.S. over the last half century. In this sub-section, we

[A7]Regressing the Deming *Routine* task content of an occupation on the occupation's *STS* and *FINGDEX* task content (weighted by 1990 population counts in each occupation) yields a coefficient on STS of 0.50 (standard error = 0.05) and a coefficient on *FINGDEX* of -0.06 (standard error = 0.06).

Figure R8: Race Gap in Disaggregated *Contact* Task Measures




*Notes:* Figure re-estimates Panel B of Figure 1 of the main text with five task components instead of four. In particular, we disaggregate *Contact* tasks into (1) *Interact* and (2) *Customer* sub-components. Only the coefficients on the *Interact* and *Customer* task measures from these yearly regressions are plotted in the figure. The sample is the same as in Panel B of Figure 1 of the main text.

explore the sensitivity of our results to using other measures of *Contact* tasks.

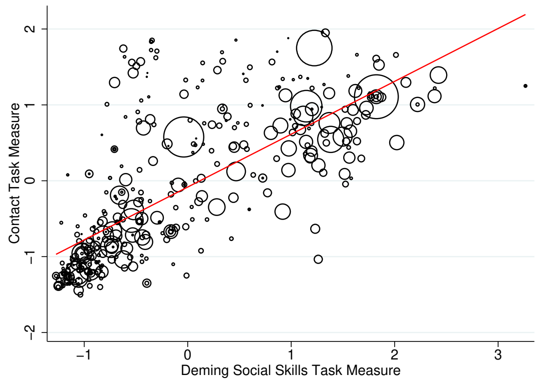
First, Appendix Figure R8 shows our key results from Figure 1 of the main text but disaggregating *Contact* into its two sub-components: *Interact* and *Customer*. The former measures the extent to which the job requires social interactions with others while the latter measures whether the job requires individuals to deal with external customers. Instead of showing all five sets of coefficients, we only show the coefficients on *Interact* tasks and *Customer* tasks.[A8] As seen from the figure, there was racial convergence in both tasks requiring contact within the firm (*Interact*) and tasks requiring contact with external customers (*Customer*). These results highlight that Blacks were moving into occupations (relatively) that require both sub-components of *Contact* tasks.

Next, we explore other potential ways to define tasks that require high degrees of contact with others. Deming (2017b) created the *Social Skills* task which measures the extent to which an occupation requires skills associated with the ability to coordinate, negotiate, and persuade others. These skills are most valuable when the job requires workers to come into contact with other co-workers, clients and customers. As a result, it is not surprising that our measure of *Contact* tasks is highly correlated with Deming's task measure of *Social Skills*. The simple correlation between Deming's *Social Skills* task measure and our *Contact* task measure is about 0.81 (weighted by 1990 population counts within each occupation). We show the simple scatter plot by occupation of the two measures in Panel A of Appendix Figure R9.

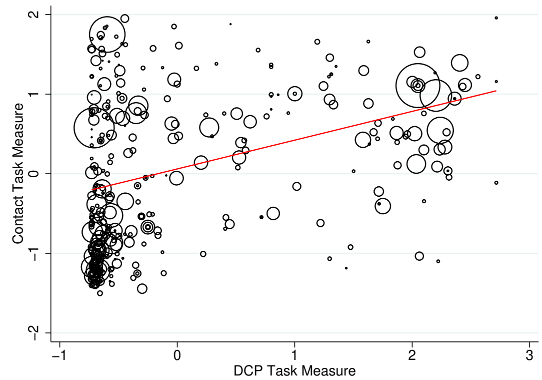
Likewise, in the DOT data, the task component *Direction, Control, and Planning of Activities (DCP)* has an interactive component to it; direction, control and planning tasks are often done to facilitate interactions with either co-workers or customers. In our base empirical work, we follow Autor and Dorn (2013) and include *DCP* as a component of *Abstract* tasks. A natural question to ask is how *DCP* correlates with our *Contact* task measure. The results

[A8] The coefficients on the other three tasks were essentially unchanged relative to Figure 1 of the main text.

Figure R9: Correlation Between Base *Contact* Task, Deming's *Social Skills* Task and *DCP* Task; Cross-Occupation Variation




PANEL A



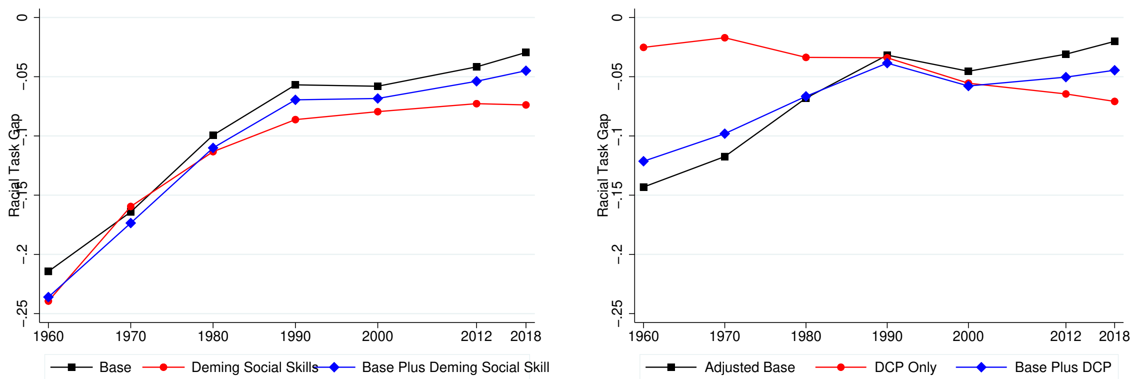

PANEL B

*Notes:* Panel A shows a scatter plot of the correlation between the *Contact* task content of an occupation and Deming's *Social Skills* task content of an occupation. Panel B shows a scatter plot of the correlation between the *Contact* task content of an occupation and DOT's *DCP* task component. Each observation in each panel is an occupation. All tasks are measured in z-score space. The size of the circle represents the number of prime age men working in that occupation in 1990. Figure also includes the weighted simple regression line through the scatter plot. The coefficient on the z-score for *Social Skills* tasks in Panel A is 0.70 (standard error = 0.05) and an adjusted R-squared of 0.65. The coefficient on the z-score for *DCP* tasks in Panel B is 0.36 (standard error = 0.08) and an adjusted R-squared of 0.21.

are shown in Panel B of Figure R9. As seen from this panel, *DCP* and our *Contact* measure are only weekly correlated with the simple correlation between the two being about 0.46 (weighted by 1990 population counts within in each occupation). Panel B suggests that our *Contact* measure is proxying for task information not contained within the *DCP* measure.

Next, we show how the trend in the racial gap in *Contact* tasks change when we measure this task using various combinations of our base measure of *Contact*, Deming's *Social Skills* task measure, and the *DCP* task measure. The results are shown across the two panels of Figure R10. In Panel A, we show the sensitivity of our results to using Deming's Social Skills task measure as component of our *Contact* task measure. For comparison, the black line (with squares) just restates our base *Contact* measure from panel B of Figure 1. The red line (with circles) re-does the analysis in Panel B of Figure 1 of the main text but replaces our base measure of *Contact* tasks with Deming's measure of *Social Skills.* The blue line (with diamonds) combines our base measure of Contact with Deming's measure of Social Skills. In particular, to compute this composite measure we take the simple average of *Interact*, *Customer*, and Deming's *Social Skills* measure for each occupation and then convert into z-score units. We refer to this as our "Base plus Social Skills" measure of *Contact* task. As seen from Panel A, all three measures track each other closely. These results highlight that our base measure of *Contact* tasks and the Deming measure of *Social Skills* tasks are highly correlated. As a result, our key results in the paper are relatively unchanged if we incorporate Deming's measure of *Social Skills* into our measure of *Contact* tasks.

Figure R10: Race Gap in *Contact* Tasks: Alternate Measures




Panel A: Deming Social Skills

Panel B: DCP

*Notes:* Figure re-estimates Panel B of Figure 1 of the main text with alternate measures of *Contact* tasks. See text for a detailed description of both panels of this figure.

In Panel B of Figure R10 we show the robustness of our results to removing *DCP* from being a component of *Abstract* tasks and replace it with *DCP* being a component of *Contact* tasks. In particular, in all of the specifications in this panel, *DCP* is removed from the measure of *Abstract* tasks; in other words, the *Abstract* task measure only includes the *GED-Math* task component. In the black line (with squares) we show the time trend in the racial gap in our base measure of *Contact* tasks. That is, this line shows the time trend in the racial gap in our base measure of *Contact* tasks when *DCP* is removed from being a component of *Abstract* tasks. In the red line (with circles) we replace our base measure of *Contact* tasks with the *DCP* task measure. In the blue line (with diamonds) we combine our base measure of *Contact* tasks with the *DCP* task measure. In particular, to compute this composite measure we take the simple average of *Interact*, *Customer*, and *DCP* task measures for each occupation and then convert into z-score units. We refer to this as our "*Base plus DCP*" measure of *Contact* task. Here the results change slightly. First, replicating the results in Figure R6, the racial gap in *DCP* tasks is small and relatively constant over time. Second, compared to the results in Panel A of this figure, the racial task gap in our base measure of *Contact* tasks is smaller in magnitude in early decades when *DCP* is removed as a component of *Abstract* tasks. Yet, even in this specification, there is a substantial convergence in the racial gap in *Contact* tasks across the decades.

Collectively, these results show that our key finding of substantial convergence in the racial gap in *Contact* tasks is robust to alternate *Contact* tasks measures. Given that our base *Contact* task measure is only weakly correlated with *DCP*, our results highlight that it is important to control for *DCP* as a separate task measure when computing the time series patterns in the racial gap in *Contact* tasks.

# Appendix D Task Gaps Across Other Groups

The main paper focuses on labor market differences between Black and White men. However, in this section of the appendix we document differences in task measures between White men and White women, as well as differences between White women and Black women. We choose to focus on Black and White men in the main paper so as to abstract from the large trends in female labor supply that have also occurred during this time period. As we show in this section, the differential trends we document for Black and White men are similar to the differential trends we find for Black and White women.

Specifically, Figure R11 shows the occupational task differences between White men and White women (panel A) and between White women and Black women (panel B) using data from the Census/ACS. This figure uses the same specification as Panel B of Figure 1 in the main text. Panel A of this appendix figure restricts the sample to native born White men and White women between the ages of 25 and 54. Panel B restricts the sample to native born White women and Black women between the ages of 25 and 54. Both panels also restrict the sample to those individuals working full time and excludes the self-employed. As with the figures in the main text, we condition on education and age when we measure the gaps in the task content of jobs.

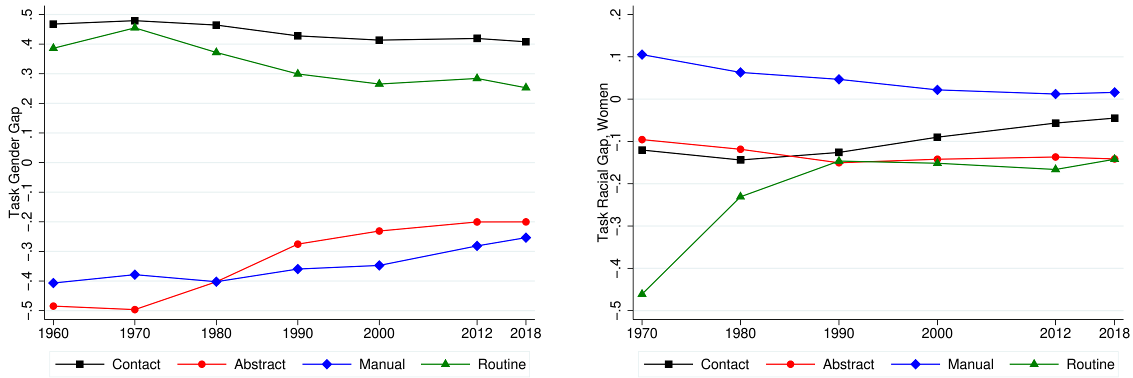
As seen from Panel A, White women are much more likely to be in *Contact* and *Routine* tasks and are much less likely to be in *Manual* and *Abstract* tasks relative to White men. Unlike the gaps between Black and White men, the gaps between White men and White women were fairly stable over the last 60 years. One exception is the gap in *Abstract* tasks. In the 1960, White women worked in occupations that required 0.5 standard deviation lower amounts of *Abstract* tasks relative to White men, conditional on age and education. By 2018, that gap fell to only about 0.2 standard deviations.

The time series patterns in Panel B between White women and Black women mirror the patterns in Panel B of Figure 1 of the main text showing differences between White men and Black men although the level gaps are smaller. The gap in the *Abstract* task content of jobs between White and Black women was roughly constant between 1960 and 2018. However, Black women converged to White women in the *Contact* task content of jobs over this period.

# Appendix E Using NLSY Data to Disentangle Racial Skill Gaps from Discrimination

In this section of the appendix, we use our structural model combined with detailed micro data from the NLSY to (i) isolate how much of the composite racial gap for *Abstract* tasks is due to racial skill gaps ($\eta^b_{kt}$) versus pecuniary discrimination ($\delta^b_{kt}$) and (ii) confirm our model prediction that the racial skill gaps do not play a role in explaining the composite racial barrier for *Contact* tasks (i.e., that all the racial *Contact* task gap is due to discrimination). According to our model, the time series trend in the composite racial gap in *Contact* tasks was entirely due to declining discrimination (i.e., falling $\gamma_{Contact,t}$) while the time series trend in the composite racial gap in *Abstract* tasks was mostly due to declining $(\eta^b_{kt} + \delta^b_{kt})$. If true, the model suggests that the declining racial gap in skills associated with *Contact* tasks ($\eta_{Contact,t}$) was not an important factor in driving the relative increase in Black men sorting

Figure R11: Task Differentials between White Men and White Women and between White Women and Black Women




Panel A: White Men vs White Women

Panel B: White Women vs Black Women

*Notes:* Figure replicates the analysis shown in Panel B of Figure 1 of the main text but does so comparing White Men and White Women (panel A) or comparing White Women and Black Women (panel B). Specifically, for the regressions in Panel A, we use the Census/ACS sample pooling together prime-age White men and women. For the regressions in Panel B, we use the Census/ACS sample pooling together prime-age White women and Black women. All samples for both regressions are also restricted to full time workers who are not self employed and who are native born. All regressions control for individual age and education dummies.

into occupations that require *Contact* tasks. Conversely, our estimated model suggests that the declining racial gap in skills associated with *Abstract* tasks (e.g., declining $\eta_{Abstract,t}$) could still be an important explanation for why the composite racial barrier for *Abstract* tasks has fallen over time. In this section, we use additional data from the NLSY to empirically assess the importance of changing racial differences in the pre-labor market skills associated with *Contact* and *Abstract* tasks.

## Appendix E.1 NLSY Skill Measures

To measure the extent to which Black and White men systematically differ in the skills needed to perform *Contact* tasks, we use the detailed measures of pre-labor market traits from the NLSY data. Specifically, we use pre-labor market measures of performance on cognitive tests and psychometric assessments for NLSY respondents to generate a set of unified proxies for cognitive, non-cognitive and social traits across the two NLSY waves. We take our definitions of these NLSY pre-labor market measures directly from the existing literature. In particular, the pre-labor market traits we use from the NLSY are taken directly from Deming (2017b). Specifically, we downloaded these variables from Deming's replication files at `https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/CYPKZH`.

***Cognitive Skills (COG)***: We follow the literature and use the respondent's scores on the Armed Forces Qualifying Test (AFQT) as our measure of cognitive skills. The AFQT is a standardized test which is designed to measure an individual's math, verbal and analytical aptitude. The test score was collected from all respondents in their initial year of the survey and was measured in both the 1979 and 1997 waves. We follow Deming (2017b) and standardize the AFQT scores so they have a mean of zero and a standard deviation of 1.[A9]

***Non-cognitive Skills (NCOG)***: We use the measures of non-cognitive skills created by Deming (2017b). Deming (2017b) uses questions pertaining to the Rotter Locus of Control Scale and the Rosenberg Self-Esteem Scale for the NLSY79 cohort to make a measure of non-cognitive skills.[A10] Likewise, for the NLSY97 cohort Deming (2017b) uses respondent answers (provided prior to entering the labor market) to the question "How much do you feel that conscientious describes you as a person?" to approximate respondents' non-cognitive skill. Deming (2017b)'s non-cognitive skill measures are expressed in z-score units.

***Social Skills (SOC)***: We again follow Deming (2017b) to generate a unified measure of social skills using a standardized composite of two variables that measure extroversion in both waves. Specifically, for the NLSY79, we use self-reported measures of sociability in childhood and sociability in adulthood. Individuals were asked to assess their current sociability (extremely shy, somewhat shy, somewhat outgoing, or extremely outgoing) and to retrospectively report their sociability when they were age 6. For the NLSY97, we proxy for social skills using the two questions that were asked to capture the extroversion factor from the commonly-used Big 5 personality inventory. For each wave, we normalize the two questions so they have the same scale and then average them together. We then convert the measures into z-score units. Deming (2017b) shows that these measures of social skills positively predict individual wages when they are adults even conditional on controlling for individual measures of cognitive skills (AFQT).

## Appendix E.2 Racial Gaps in Pre-Labor Market Skills

Table R3 reports the racial gap in cognitive, non-cognitive, and social skills with various controls for the two separate NLSY samples. The first column for each sample includes all NLSY respondents in the sample without conditioning on employment; each of these samples has only one NLSY respondent per regression. The remaining columns pool over all years and only include individuals who were employed. The second column within each sample adds no further controls, while the third column controls for the individual's maximum level of education. The main takeaway from this table is that the racial gap in cognitive skills (AFQT scores) is large and narrows over time, whereas the racial gap in social skills is relatively small and is roughly constant over time.[A11]

[A9]The AFQT score has been used by many in the literature to measure respondent's cognitive skills including Neal and Johnson (1996), Heckman et al. (2006), Neal (2006), Altonji et al. (2012) and more recently Levine and Rubinstein (2017) and Deming (2017b). Altonji et al. (2012) developed a mapping of the AFQT score across the NLSY79 and NLSY97 waves that accounts for differences in age-at-test and test format. Deming (2017b) used these harmonized test scores in his analysis (which we download for our analysis).

[A10]The Rotter scale measures the degree of control individuals feel they possess over the life. The Rosenberg scale measures perceptions of self-worth. Higher values of both are interpreted as high levels of non-cognitive skills. For example, Heckman and Kautz (2012) documents notable associations between educational attainment, health and labor market performance and these non-cognitive measures using NLSY data.

[A11]When using these skill measures, it is important to keep in mind that there are not innate differences in "skill" levels across racial groups. To the extent that such skill differences are found, they almost certainly result from current and past discrimination.

Table R3: Racial Gaps in NLSY Pre-Labor Market Skill Measures (Z-Score Differences)

| | 1979 Cohort | | | 1997 Cohort | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| (A) Cognitive Skills | -1.17 | -1.18 | -1.00 | -0.96 | -0.82 | -0.64 |
| | ( 0.03) | ( 0.04) | ( 0.03) | ( 0.05) | ( 0.06) | ( 0.05) |
| (B) Non-Cog. Skills | -0.20 | -0.18 | -0.09 | 0.11 | 0.06 | 0.10 |
| | ( 0.04) | ( 0.04) | ( 0.04) | ( 0.05) | ( 0.07) | ( 0.07) |
| (C) Social Skills | -0.09 | -0.11 | -0.08 | -0.16 | -0.14 | -0.14 |
| | ( 0.04) | ( 0.04) | ( 0.04) | ( 0.05) | ( 0.06) | ( 0.06) |
| Employed Only Sample | No | Yes | Yes | No | Yes | Yes |
| Education Controls | No | No | Yes | No | No | Yes |
| Sample Size Clusters | 4,226 | 3,705 | 3,705 | 2,375 | 1,901 | 1,901 |
| Sample Size Observations | 4,226 | 22,597 | 22,597 | 2,375 | 8,219 | 8,219 |

Note: Table shows the racial gap in various NLSY skill measures for various samples and with various controls. We show results separately for the 1979 cohort (columns (1)-(3)) and the 1997 cohort (columns (4)-(6)). Cognitive skills are measured as normalized AFQT scores. All racial gaps are measured in z-score differences between Black and White men. Columns (1) and (4) shows results for all individuals regardless of employment status; in these specifications each individual is only in the sample once. In the remaining columns we condition on the individual being employed in a given year. In these specifications, individuals can be in the sample multiple times. Robust standard errors are in parentheses.

## Appendix E.3 A Procedure to Estimate Racial Differences in Task-Specific Skills ($\eta_{kt}$'s)

While much research has focused on accounting for individual pre-labor market traits in explaining racial wage gaps using the NLSY data (e.g., Neal and Johnson (1996)), our framework emphasizes workers' *task-specific skills*, i.e., skills associated with *Abstract*, *Contact*, and *Routine* tasks. We next lay out the procedure for translating the racial gaps in NLSY pre-labor market traits into racial gaps in task-specific skills. The procedure utilizes information on how NLSY pre-labor market traits predict subsequent occupational sorting along task dimensions when the respondents become adults.

Specifically, our procedure mapping individual measures of pre-labor market traits from the NLSY into model-based measures of task-specific skills has two steps. First, restricting ourselves to the sample of White men, we map NLSY measures of cognitive, non-cognitive, and social traits into task-specific skills in the model (up to a scalar) using the following regression:

$$\overline{\phi}_{kt}^{wo} = a_{kt} + b_{cog,kt}\overline{S}_{cog,t}^{wo} + b_{ncog,kt}\overline{S}_{ncog,t}^{wo} + b_{soc,kt}\overline{S}_{soc,t}^{wo} + \epsilon_{kt}^{wo}, \quad \text{(R2)}$$

where the dependent variable $\overline{\phi}_{kt}^{wo}$ is the occupational-average of task-specific skills for task $k$ in period $t$, $\phi_{kt}$, averaged across White men $w$ working in occupation $o$ generated by the model. The regressors are the empirical measures of the occupational-average of cognitive ($\overline{S}^{wo}_{cog,t}$), non-cognitive ($\overline{S}^{wo}_{ncog,t}$) and social traits ($\overline{S}^{wo}_{soc,t}$) averaged across White men ($w$) in the corresponding occupation $o$ from our sample of NLSY respondents during year $t$. For this analysis, we use the same 66 broad occupations from the model estimation. Intuitively, this first stage regression produces a weighting (the $b$'s) of NLSY individual pre-labor market traits for each task-specific skill ($\phi_{kt}$) by exploiting cross-occupation variation for White men in both the model and the data. For example, the first stage regression assesses whether occupations where the individuals have relatively more cognitive traits in the NLSY are also the occupations where individuals have relatively more *Abstract* skills in the model. We estimate this first stage equation separately for each of the model's $K$ task-measures (*Abstract*, *Contact* and *Routine* tasks).

In the second stage of our procedure, we impute the racial gaps in task-specific skills in each occupation using the estimated coefficients for White men from equation (R2) along with the Black-White gaps in measured individual pre-labor market traits within each occupation from the NLSY. Define $\overline{S}^{gap,o}_{cog,t}$, $\overline{S}^{gap,o}_{ncog,t}$, and $\overline{S}^{gap,o}_{soc,t}$ as the racial gaps in cognitive, non-cognitive, and social skills in each occupation $o$ using micro data from the NLSY in each year $t$, respectively. Formally, using the coefficients $\hat{b}_{cog,kt}$, $\hat{b}_{ncog,kt}$, and $\hat{b}_{soc,kt}$ from the first stage regression, we predict the average occupational racial gap in task-specific skills in model units – which we denote $\widehat{\phi}^{gap,o}_{kt}$ – based on the empirically observed racial gap in skills within each occupation using micro data from the NLSY:

$$\widehat{\phi}^{gap,o}_{kt} = \hat{b}_{cog,kt}\overline{S}^{gap,o}_{cog,t} + \hat{b}_{ncog,kt}\overline{S}^{gap,o}_{ncog,t} + \hat{b}_{soc,kt}\overline{S}^{gap,o}_{soc,t}\,. \tag{R3}$$

Once we obtain the NLSY-based predictions, we infer the $\eta^b_{kt}$'s that make the model-generated $\overline{\phi}^{gap,o}_{kt}$'s consistent with the NLSY-based predicted $\widehat{\phi}^{gap,o}_{kt}$'s. In sum, our procedure just ensures the model estimate of the racial skill gaps matches the weighted average of the racial gaps in NLSY skills separately for each task where the weights are estimated in the first stage. We then attribute the residual pecuniary task-specific barriers facing Black men ($\eta^b_{kt}+\delta^b_{kt}$) to pecuniary discrimination ($\delta^b_{kt}$'s) after accounting for racial skill differences ($\eta^b_{kt}$'s).

## Appendix E.4 Estimating the First Stage of our Procedure

In terms of implementation, we map the model estimates from 1990 to the data for the NLSY-79 cohort; given our age restrictions, 1990 is about the average year of data for the NLSY-79 cohort. Likewise, we map the model estimates from 2012 to the data from the NLSY-97 cohort. When estimating (R2) for our first stage regression, we again use cross-occupational variation aggregating the data to 66 unique broader occupations within each year. We pool together the data from the NLSY-79 (1990) and the NLSY-97 (2012) when estimating the first stage equation.

Estimates from our first stage regressions are shown in Table R4. The table reports the first stage mapping for *Abstract* (column 1), *Contact* (column 2) and *Routine* tasks (column 3) for White men. Each column reflects the estimates of $b_{cog,kt}$'s, $b_{ncog,kt}$'s, and $b_{soc,kt}$'s from separate regressions of equation (R2) for the various tasks. A few things are of note from Table R4. First, cognitive skills are most predictive of the skills required for *Abstract* tasks. Occupations where workers have high cognitive skills on average in the NLSY are also the occupations where the model predicts that workers have higher levels of *Abstract* task-specific

Table R4: First Stage Regression of Average Model Task Skills on Average NLSY Individual Skills, Cross-Occupation Variation

| | *Abstract* | *Contact* | *Routine* |
|---|---|---|---|
| Cognitive | 0.31 | 0.10 | -0.09 |
| | ( 0.06) | ( 0.02) | ( 0.06) |
| Non-Cognitive | 0.37 | -0.01 | -0.02 |
| | ( 0.15) | ( 0.04) | ( 0.09) |
| Social | -0.19 | 0.26 | -0.14 |
| | ( 0.14) | ( 0.07) | ( 0.10) |
| Year Fixed Effects | Yes | Yes | Yes |
| Adj. R-Squared | 0.43 | 0.39 | 0.05 |
| F-Stat | 15.3 | 13.0 | 2.3 |

*Notes:* Table shows estimate coefficients from first stage regression equation (R2) for White men. Each column is a separate regression exploiting cross-occupation variation. We use 66 broad occupation categories. For these regressions, we pool together observations 1990 and 2012 so that each regression will have 132 observations (2*66). See the text for additional details.

skills. Second, social skills are only positively predictive of the skills required for *Contact* tasks. Social skills, conditional on cognitive and non-cognitive skills, are not positively related to the skills required for *Abstract* and *Routine* tasks; the coefficients for both are actually negative and statistically insignificant from zero. Third, our first stage procedure has sizable F-stats for both *Abstract* and *Contact* tasks. However, we have little first-stage power predicting *Routine* tasks. In sum, despite these skill measures coming from relatively narrow survey questions in the NLSY, the skill measures are quite predictive of task-specific occupational sorting for *Abstract* and *Contact* tasks when viewed through the lens of the model. This predictive power gives us confidence with respect to performing the decomposition exercises for these tasks below.

Given the NLSY data with skill measures do not extend back to 1960, we need to make assumptions about the projection in 1960 if we want to discuss components of the racial task gaps prior to 1990. Specifically, for our 1960 decomposition, we assume that the racial differences in NLSY skill levels in the South in 1990 can be used as a proxy for the racial skill differences nationally in 1960. There is some existing empirical support for this assumption. Chay et al. (2009) using data from National Assessment of Educational Progress finds a Black-White gap in standardized cognitive test scores for a nationally representative sample of individuals born between 1953 and 1961 of about -1.25 standard deviations. For male NLSY79 respondents in the South, we find an unconditional AFQT racial gap of about -1.2 standard deviations. The fact that the Black-White gaps in cognitive test scores for men in the NSLY79 cohort are roughly similar to the Black-White gaps in cognitive test scores for the U.S. as a whole in 1960 gives us some confidence in using our imputation procedure to

Table R5: Decomposition of Racial Barrier to *Contact* and *Abstract* Tasks

| | Panel A: *Contact* Tasks | | | | Panel B: *Abstract* Tasks | | | |
|---|---|---|---|---|---|---|---|---|
| | 1960 | 1990 | 2012 | Change | 1960 | 1990 | 2012 | Change |
| $\delta + \eta + \gamma$ | -0.82 | -0.30 | -0.20 | 0.62 | -0.86 | -0.41 | -0.41 | 0.45 |
| $\eta$ | -0.16 | -0.12 | -0.11 | 0.05 | -0.43 | -0.35 | -0.19 | 0.24 |
| $\delta + \gamma$ | -0.66 | -0.18 | -0.08 | 0.57 | -0.43 | -0.06 | -0.22 | 0.21 |
| $\gamma$ | -0.89 | -0.33 | -0.16 | 0.73 | 0.02 | -0.06 | -0.02 | -0.04 |

*Notes:* Table shows model decomposition of racial differences in $(\eta^b_{kt}+\delta^b_{btk}+\gamma^b_{kt})$ into its components for *Contact* tasks (Panel A) and *Abstract* tasks (Panel B) in 1960, 1990, and 2012 using our decomposition procedure.

infer 1960 relationships.

## Appendix E.5 Decomposing Racial Gaps in *Contact* Tasks

Panel A of Table R5 shows the results of our decomposition procedure for *Contact* tasks. The first row reports the time series trend in our composite racial barrier for *Contact* tasks estimated in Section 5 of the main text; these are the same values as the ones shown in the black line (with squares) in Figure 5 of the main text. The second row reports our decomposition procedure's estimate of $\eta_{Contact,t}$ while the third row reports our estimates of direct discrimination ($\delta_{Contact,t} + \gamma_{Contact,t}$). The final row re-reports our estimate of just the non-pecuniary discrimination term, $\delta_{Contact,t}$; these are the same values as the ones shown in the red line (with circles) in Figure 5 of the main text.

A few key results are notable with respect to our decomposition for *Contact* tasks. First, our model attributes essentially all of the racial gap in *Contact* tasks in 1960 to direct discrimination, ($\delta + \gamma$); Black men in 1960 were underrepresented in occupations requiring *Contact* tasks primarily because they were discriminated against in those tasks. Second, between 1960 and 1990, direct discrimination associated with *Contact* tasks fell sharply. Moreover, essentially all of the decline in the composite racial barrier for *Contact* tasks can be attributed to the decline in ($\delta_{Contact,t} + \gamma_{Contact,t}$). By 2012, the model estimates only a small amount of remaining discrimination in *Contact* tasks. As highlighted in Table 2, essentially all of the decline in discrimination estimated for *Contact* tasks was due to a decline in non-pecuniary discrimination (i.e., a sharp decline in $\gamma_{Contact,t}$). Finally, our model also estimates that there is a small racial skill gap associated with *Contact* tasks, $\eta_{Contact,t}$, that has remained relatively constant over time.

What are the empirical underpinnings that are driving our decomposition results that find that racial skill gaps are not an important driver of the composite racial barrier for *Contact* tasks? First, recall that the NLSY measures of social traits are most predictive of skills required for *Contact* tasks for White men and that the racial gap in social traits in the NLSY is small in all years. Second, according to the NLSY data, cognitive traits (AFQT) only have modest predictive power for skills required for *Contact* tasks. Given that there is a large racial gap in cognitive traits, our procedure estimates a non-zero $\eta_{Contact,t}$. However, because cognitive skills only have modest effect predicting skills required for *Contact* tasks, changes in the racial gap in cognitive skills over time does not meaningfully contribute to changes in the composite racial barrier for *Contact* tasks over time.

Given these factors, our procedure concludes that the racial gap in *Contact* tasks is not driven by racial skill gaps; instead, we find that the racial gap in *Contact* tasks is good proxy for the extent of direct discrimination in the economy. The analysis bringing in data from the NLSY provides additional support for the findings of our baseline structural model that the racial gap in *Contact* tasks is primarily driven by discrimination as opposed to a racial gap in the skills associated with *Contact* tasks.

Panel B of Table R5 shows the results of our decomposition procedure for *Abstract* tasks. Unlike with *Contact* tasks, our decomposition procedure attributes most of the racial barrier associated with *Abstract* tasks in 1960, 1990 and 2012 to racial differences in skills. Underlying this estimate is the fact that we find that (i) cognitive skills strongly predict skills required for *Abstract* tasks for White men and (ii) there are large racial gaps in cognitive skills among NLSY respondents. Our baseline model in the main paper highlights that the racial gap in *Abstract* tasks is driven by $(\eta^b_{kt} + \delta^b_{kt})$ as opposed to $\gamma_{kt}$. By bringing in data from the NLSY and using our procedure to merge in the NLSY data into our model, we find that $\eta^b_{kt}$ – the racial gap in skills associated with *Abstract* tasks – is important for explaining both the level and trend in the composite racial barrier for *Abstract* tasks over time. However, it should be noted that we are also finding that changes in pecuniary direct discrimination ($\delta_{Abstract,t}$) is also potentially important in explaining changes in the composite task barrier for *Abstract* tasks over time; given the racial skill gap for skills associated with Abstract tasks, this force could represent statistical discrimination (as discussed more detail in Appendix G).

To summarize, by bringing in the NLSY data we find further support that the time series trend in the racial gap in *Contact* tasks is almost exclusively driven by changes in direct measures of discrimination over time (as opposed to trends in the racial skill gap associated with *Contact* tasks). Conversely, bringing in the NLSY data finds that about half of the level and trend in the composite racial gap for *Abstract* tasks is driven by the racial gap in skills associated with *Abstract* tasks.

## Appendix E.6 Additional Discussion

Before concluding this section, we discuss how any misspecification in our decomposition equations (R2) and (R3) can bias our estimates of the change in our estimated task-specific $\eta^b_{kt}$'s over time. In particular, if there is an omitted trait not measured in the NLSY that predicts an individual's task-based skills, and if that omitted variable changes differentially between Black and White men over time, our estimates of $\Delta\eta^b_{kt}$ between two periods will be biased. There is some evidence that this may be the case. For example, Rodgers and Spriggs (1996) finds that the wage return to cognitive skill measures from the NLSY differs between Black and White men.[A12] Give this, we perform various exercises to assess whether such

[A12] We find similar evidence in our sample of NLSY respondents even conditional on education and occupation.

omitted skills could be an issue. We highlight two such exercises here.

First, reduced-form regressions from the NLSY show that cognitive skills when young strongly predict the *Abstract* task content of an individual's occupation when they are older for *both* Black and White men. For our key results, it is important that AFQT scores predict occupation choice for both Black and White men. In particular, we run the following regression separately for both Black and White men:

$$\tau_{o(i),Abstract} = \alpha + \chi_{cog} S_i^{cog} + \chi_{ncog} S_i^{ncog} + \chi_{soc} S_i^{soc} + \Gamma X_i + \epsilon_i \tag{R4}$$

where $\tau_{o(i),Abstract}$ is the *Abstract* task content of a worker $i$'s occupation when they are between 25 and 54, and $S_i^{cog}$, $S_i^{ncog}$, and $S_i^{soc}$ are individual $i$'s cognitive, non-cognitive, and social skills when in high school, respectively. The regression coefficient $\chi_{cog}$ therefore measures whether individuals with more cognitive skills when young are more likely to sort into occupations requiring more *Abstract* tasks when older. Again, we estimate this regression separately for Black and White individuals. For this estimating regression, we pool together data from both the 1979 and 1997 waves of the NLSY. We include all individuals between the ages of 25 and 54; given this, the same individual can be in the regression multiple times. Included in the regression is a vector of controls, $X$, which includes the individual's age, dummies for their level of educational attainment, dummies for the NLSY wave, and year fixed effects.

The results of these regressions are shown in Appendix Table R6. The coefficient from our regression for White men are shown in column (1) while the coefficients from our regression for Black men are shown in column (2). We show the difference in coefficients in column (3). As seen from the table, individuals with higher cognitive skills (AFQT score) when young are much more likely to enter occupations requiring relatively more *Abstract* tasks when old. This relationship is very similar for both Black and White men. Collectively, these patterns highlight that cognitive skills are strongly predictive of entry into occupations that are relatively more *Abstract* intensive for *both* Black and White men. This gives us some confidence that the procedure we developed above in terms of combining our model structure with the NLSY data to back out the $\eta_{kt}^b$'s for *Abstract* tasks.

# Appendix F Model Fit, Additional Model Validation and Additional Model Results

In this section of the appendix, we show additional results on how well our estimated model matches both additional targeted and non-targeted moments.

## Appendix F.1 Model Fit

Figure R12 compares the key model moments (solid lines) against the corresponding data targets (dashed lines). As seen from the various panels of the figure, our model generally fits the data quite well. For panels C and D, the dashed and solid lines are on top of each other. The model fit for the racial gap in the *Manual* task content of jobs – the moment we do not target – is naturally less tight (not shown), but nonetheless the model is able to match the fact that the racial gap in *Manual* tasks is close to zero. This makes us confident that

Table R6: Racial Differences in the Relationship between Relative Abstract Content of Occupation During Working Years and Pre-Labor Market Traits, NLSY

| | White Men | Black Men | Difference |
|---|---|---|---|
| *Cognitive* | 0.216 | 0.214 | -0.002 |
| | ( 0.019) | ( 0.024) | ( 0.031) |
| *Non-Cognitive* | 0.041 | 0.025 | -0.015 |
| | ( 0.016) | ( 0.020) | ( 0.025) |
| *Social* | 0.037 | 0.022 | -0.015 |
| | ( 0.015) | ( 0.016) | ( 0.022) |
| Observations | 30,753 | 13,639 | |
| Adjusted R-squared | 0.284 | 0.293 | |

Note: Table shows coefficients on cognitive, non-cognitive, and social pre-labor market traits from equation (R4) above. Estimation uses micro data from the NLSY. We regress the relative *Abstract* task content of the occupation where the NLSY respondent works when they are older on their pre-labor market cognitive, non-cognitive and social skills measured when young. We estimate the equation separately for Black and White men. All regressions include controls for the individual's age and education as well as a series of fixed effects for the NLSY survey wave and the year of the observation. Robust standard errors clustered at the individual level are shown in parentheses.

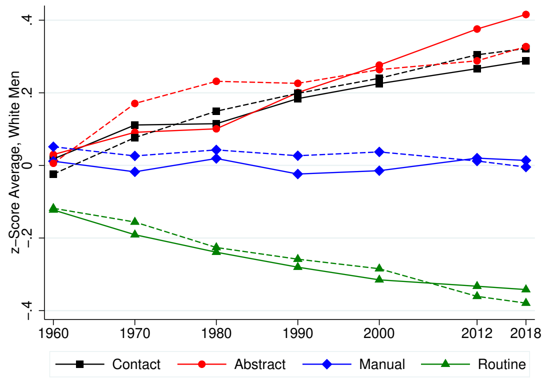
our assumption that racial barriers in *Manual* tasks are zero (which we impose because the estimated $\beta_{kt}$ for *Manual* tasks is equal to or very near zero in all years) has little impact on our key paper results.

## Appendix F.2 Additional Model Validation

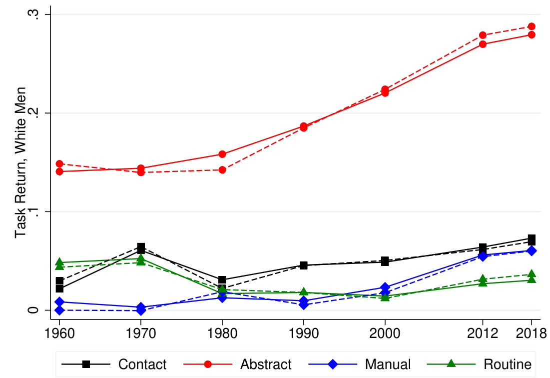
The model results we explore in the paper rely on the functional form assumptions we made for the various distributions from which individuals draw task-specific skills or occupational preferences. In this subsection of the appendix, we explore whether such distributional assumptions are grossly at odds with the data by assessing the extent to which our estimated model matches other non-targeted moments.

When estimating our model, we targeted the mean wage gap between Black and White men as one of our key moments. We now explore how our model performs in matching the trends in racial wage rank gaps for different percentiles as documented by Bayer and Charles (2018). Specifically, we compute (separately by year) the median and 90th percentile of the Black wage distribution, and find out the positions of these Black wages in the White wage distribution. The differences in positions of these Black wages in Black and White distributions constitute the "wage rank gaps" at the median and 90th percentile, respectively. For example, a relative wage rank gap of -30 for the median series implies that the median wage of Black men is at the 20th percentile of the White men wage distribution or 30 percentage points lower than the

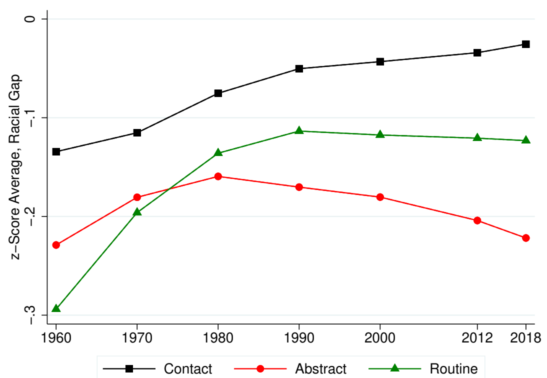
Figure R12: Model versus Data Moments



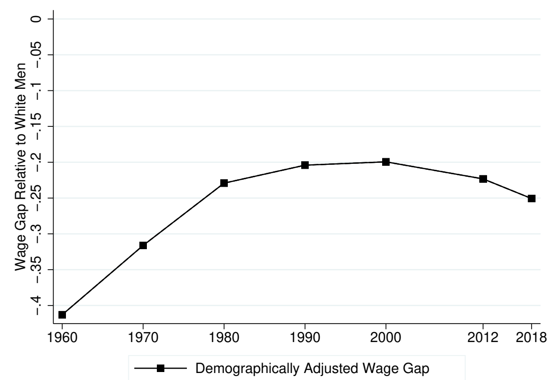

Panel A: Task Contents, White Men




Panel B: Task Prices, White Men




Panel C: Task Contents, Gap



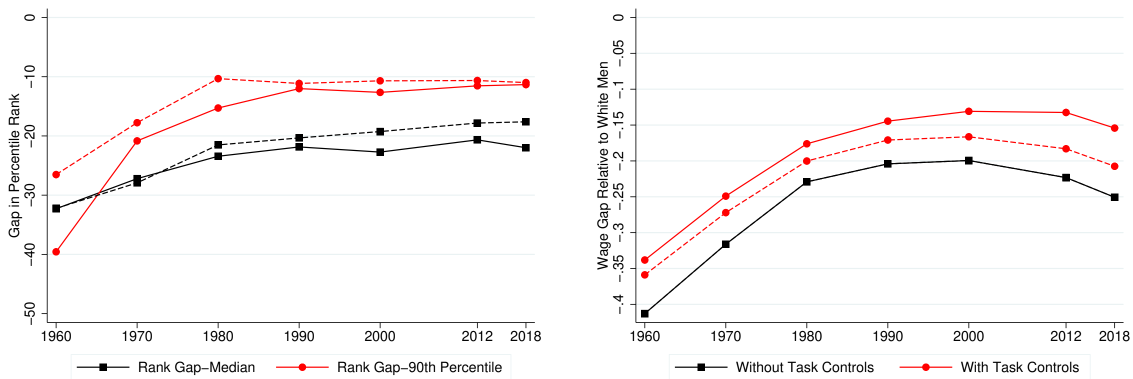

Panel D: Aggregate Wage Gap

*Notes:* Figure shows how selected model moments (solid lines) compare to their corresponding data moments (dashed lines). The data moments are the ones used as targets for the model to match. Panels A and B are data for White Men and are unconditional on education. Panels C and D are the racial gaps in wages and task content of occupations conditional on age and education.

median. Likewise, a relative rank gap of -30 for the 90th percentile series implies that the 90th percentile in the Black man wage distribution is at the 60th percentile of the White man wage distribution. For this analysis, we follow Bayer and Charles (2018) and include both working and non-working individuals in our analysis with the wages of non-working individuals set to zero.

Panel A of Appendix Figure R13 shows our results. The dashed black line (with squares) represents the relative racial rank gap for the median series while the dashed red line (with circles) represents the relative rank gap for the 90th percentile, both using our Census/ACS data. The black and red solid lines, respectively, show the analogs from the model. It should be noted that the empirical findings from the Census/ACS data in Panel A are similar to those documented in Bayer and Charles (2018). The median Black man in 1960 had a wage that was equal to the 20th percentile of the White wage distribution. Between 1960 and 2018, the relative rank gap of the median Black made little progress. Between 1980 and 2018, the median Black man had wages that was equal to about the 30th percentile of the White wage distribution. Conversely, much more relative progress was made for Blacks at the top of the

Figure R13: Model Performance Against Non-Targeted Empirical Moments




Panel A: Racial Gap in Percentile Rank of Wages

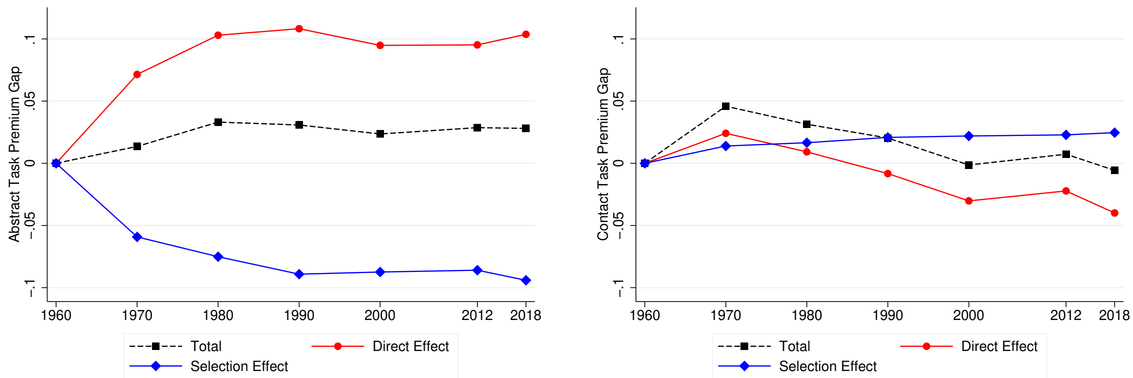
Panel B: Racial Wage Gaps Conditional on Tasks

*Notes:* Panel A shows the model implied racial rank gaps for different percentiles against their empirical analogs. In particular, the solid black line (with squares) shows the relative rank gap. Panel B shows model based estimates (solid lines) and data estimates from the Census/ACS (dashed lines) of demographically adjusted racial wage gaps with and without controlling for the task content of occupations.

wage distribution. In 1960, the 90th percentile of the Black wage distribution was at about the 60th percentile of the White wage distribution. By 2018, the 90th percentile of the Black wage distribution had a value that was equal to roughly the 80th percentile of the White distribution. However, even for the 90th percentile, little progress was made in the racial rank gap since 1980. Notice, our model (in solid lines) roughly matches these patterns even though they were not targeted. This suggests that model driving forces and racial sorting that we estimate can explain relative racial wage patterns throughout the wage distribution.

Panel B of Appendix Figure R13 shows the demographically-adjusted racial wage gap (Black lines with squares) and the racial wage gap conditional on task controls (red lines with circles), where the solid lines are model-implied and the dashed lines are their data analogs using the Census/ACS samples. Specifically, to get the red lines we regress the log wages on a race dummy and the $\tau_{jk}$'s for each of the four tasks, separately for each year, first with the model-generated data and then with the Census/ACS data. As the comparison of the black and red solid lines reveals, the model predicts that controlling for occupational tasks only has a small effect on the estimated racial wage gap. This model finding closely matches what we find in the data. Again, these results were not targeted when estimating the model. The similarity stems from the fact that the sorting on skills in the model is close to the sorting on skills in the data. Collectively, the fact that our estimated model matches a variety of non-target moments gives us confidence in the model findings we highlight next.

Figure R14: Cumulative Contributions to Changes in Racial Task Premium Gaps for *Contact* and *Abstract* tasks




Panel A: Abstract Tasks

Panel B: Contact Tasks

*Notes:* Dashed lines show the reduced form empirical estimates of the racial gap in task returns for *Abstract* tasks (Panel A) and *Contact* tasks (Panel B). These estimates are the same as those in Panel C of Figure 3 of the main text. The solid line blue line (with squares) uses the model to compute how the racial gap in task returns evolve due to differential trends in selection between Black and White men. The solid red line (with circles) shows how the racial gap in task returns would have evolved holding selection constant.

## Appendix F.3 Selection and Evolution of Racial Gaps in Task Premiums

In Section 5, we saw that selection plays a large role in *Abstract* tasks but much less so in *Contact* tasks. Recall that we estimated a large pecuniary barrier in *Abstract* tasks but only a small pecuniary barrier in *Contact* tasks despite the racial gaps in task premiums being near zero for both tasks throughout the period. The contrasting estimates arose because of the differences in the extent of selection on task-specific skills that underlay the task premium gaps. The large composite racial barrier in *Abstract* tasks implied that there was strong selection on *Abstract* skills; this masked a large pecuniary barrier in the task. In contrast, selection on *Contact* skills was much weaker and hence the racial gap in *Contact* task premium – which was close to zero throughout – closely reflected the underlying pecuniary barrier in the task (or, rather, its absence).

One can ask a similar question with respect to trends: how can we estimate a large decline in the pecuniary barrier in *Abstract* tasks over the 1960-1980 period when the corresponding racial gap in *Abstract* task premium shows no such trend? The answer again lies in selection. Figure R14 decomposes the cumulative changes over time in the racial gaps in task premiums for *Abstract* tasks (Panel A) and *Contact* tasks (Panel B) from 1960 onward (dotted black line) into the direct effects of changing task prices $\beta_{kt}$ and pecuniary barriers $\delta^b_{kt} + \eta^b_{kt}$ (solid red line) and the contributions of changing selection forces (solid blue line).[A13]

[A13]The decomposition employs the same methodology as the one we used to decompose the evolution of the racial wage gap and the racial task content gaps into parts due to race-neutral and race-specific forces

Panel A highlights that selection on *Abstract* skills weakened over the 1960-1990 period, widening the *Abstract* task premium gap and thereby masking the effect of the large estimated decline in pecuniary barriers in *Abstract* tasks. Said differently, we estimate a large decline in the pecuniary barrier $\delta^b_{kt} + \eta^b_{kt}$ in *Abstract* tasks from 1960 to 1980 despite the roughly constant gap in *Abstract* task premiums because of the declining selection on *Abstract* skills. The decline in the composite racial barrier $\delta^b_{kt}+\eta^b_{kt}+\gamma^b_{kt}$ in *Abstract* tasks – which we infer from the convergence in the *Abstract* task content gap – implies a decline in selection on *Abstract* skills over the period. Had there not been a decline in the pecuniary barrier in *Abstract* tasks, we would then have seen a widening of the racial gap in *Abstract* tasks premium.

In contrast, Panel B shows little trend in the selection on *Contact* skills. Combined with the roughly constant racial gap in *Contact* task premium, this implies that there could not have been much trend in the pecuniary barriers in *Contact* tasks, including the racial skill gap in *Contact* tasks. Had there been a large decline in the racial gap in *Contact* task-specific skills, then we would have seen the racial gap in *Contact* task premiums turn into a large positive. This explains our key finding that non-pecuniary discrimination explains almost all of the changes in the composite racial barrier in *Contact* tasks over time.

One might be concerned that the finding above – namely that the selection on *Contact* skills changed little over time – might depend on our distributional assumptions regarding skills and idiosyncratic occupational preferences. In the next subsections, we show our qualitative findings are robust to alternative distributional assumptions, i.e., choices of $\psi$ and $\theta$.

## Appendix F.4 Robustness to Alternate $\psi$'s

Next, we explore the robustness of our key results to alternative values of the Frechet shape parameter $\psi$ for idiosyncratic occupational preferences. Recall from Section 4 that we externally set the value of $\psi$ to obtain an empirically realistic elasticity for the labor supply. Specifically, as we show in Appendix H, we have the following relationship between the extensive-margin elasticity of labor supply $\varepsilon^g_t$ and the employment rate $L^g_t$ under reasonable values of $\psi$ and $\theta$:

$$\varepsilon^g_t = \psi\,(1 - L^g_t) - \psi\,\sigma^2_{L^g_t},$$

where $\sigma^2_{L^g_t} \geq 0$ is a term that is quantitatively negligible under reasonable parameterizations.[A14] The non-employment rate $1 - L^g_t$ for White men is about 11% on average over the 1960-2018 period in the data. We thus set $\psi = 4.5$ as our baseline to roughly match the extensive margin labor supply elasticity of 0.5, which is within the range of labor supply

in Section 5.2. In particular, we decompose the total derivative of the racial task premium gap into three components. First, the direct effect measures the change in the task premium gap due to changing $\beta_{kt}$'s and $\delta^b_{kt} + \eta^b_{kt}$'s holding sorting and selection fixed. Second, the selection effect measures the change in the gap due to changing racial skill differences within each occupation (i.e., the differences in the average skill in each occupation $\bar{\phi}^g_{okt}$, holding employment shares of each occupation and the average pay in each occupation fixed). Third, the sorting effect measures the change in the gap due to changing employment shares of each occupation, holding the average skill level and the average pay in each occupation fixed. Finally, we integrate each of the three components of the total derivative over time linearly interpolating parameters over time. The figure shows the direct and selection effects; the sorting effect (not shown) is relatively small.

[A14] The exact expression is given in Appendix H.

elasticity estimated in the literature (Chetty et al. (2013)).[A15] Nonetheless, our conclusions are qualitatively robust to other reasonable values of $\psi$. In the following, we present the key results of the paper when we re-estimate the model setting $\psi = 3.5$ (which corresponds to $\varepsilon_t^g \approx 0.4$) and $\psi = 5.5$ (which corresponds to $\varepsilon_t^g \approx 0.6$).

The first of our key contributions is to show that racial barriers in *Contact* tasks provide a good proxy for direct discrimination. Figure R15 shows the robustness of this result by reproducing Figure 5 – which plots the model estimates of task-specific racial barriers – under the alternate values of $\psi$'s. Specifically, the figure plots our model estimates of the composite racial barrier $(\eta_{kt}^b + \delta_{kt}^b + \gamma_{kt}^b)$ and the component that is due to non-pecuniary discrimination $(\gamma_{kt}^b)$ for *Contact* tasks (Panels A and B) and *Abstract* tasks (Panels C and D); Panels A and C show the estimates under $\psi = 3.5$, while Panels B and D show the estimates under $\psi = 5.5$. The comparison of Panels A and B shows that regardless of whether we set $\psi$ to 3.5 or 5.5 the racial barrier in *Contact* tasks is driven primarily by non-pecuniary discrimination, both in level and in trend. In contrast, pecuniary barriers $\delta_{kt}^b + \eta_{kt}^b$ explain a large part of the composite racial barrier in *Abstract* tasks, again regardless of the choice of $\psi$.

To gain intuition, recall that the estimates of pecuniary task barriers $\delta_{kt}^b + \eta_{kt}^b$ reflect the degree of selection on skills given that the observed racial gaps in the Mincerian task premiums are close to zero. Note also that a higher value of $\psi$ corresponds to a thinner tail for the occupational preference distribution and thus reduced sorting friction. Consider how this reduction in sorting friction affects the degree of selection on skills. On the one hand, the reduced sorting friction implies smaller estimates of the composite racial task barriers for given empirical sorting differences by race. This reduces selection. On the other hand, the reduction in sorting friction also implies more selection for a given level of the composite racial task barrier. This increases selection. Overall, these two forces offset each other and the degree of selection on skills does not change much, delivering stable estimates of $\delta_{kt}^b + \eta_{kt}^b$ relative to the overall composite racial tack barriers.

The second of our main contributions is to show that the rising *Abstract* task returns post-1980 underlay the stagnation of the racial wage gap post-1980. Figure R16 reproduces Figure 7 – which shows the cumulative contributions of changing race-neutral and race-specific forces to the evolution of the racial wage gap – under the alternative $\psi$ values, $\psi = 3.5$ (Panel A) and $\psi = 5.5$ (Panel B). The results are almost identical across the two panels. This is because, as suggested in the discussion of Corollary 1, the effect of changing $\beta$'s on the aggregate racial wage gap is primarily driven by the current racial gaps in pay and sorting – which we target in the estimation – rather than by the sorting *responses* to changing parameters, for which the value of $\psi$ matters. This also explains why our model estimates are roughly similar to the results implied by the model-guided empirical exercises in Section 6.

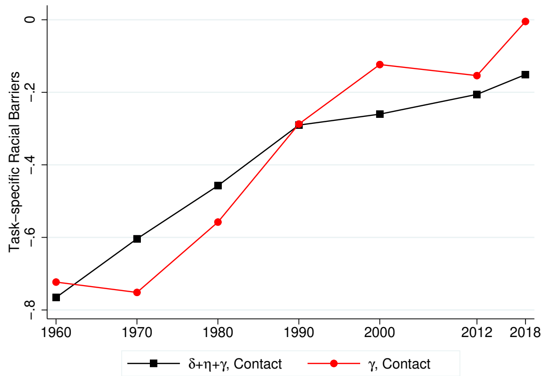
Overall, we conclude that both of our two key contributions are robust to alternative values of $\psi$'s within a reasonable range.

## Appendix F.5 Robustness to Alternate $\theta$'s

Finally, we explore the robustness of our results to alternative values of $\theta$, the shape parameter for the skill distributions. Recall that $\theta$ controls the thickness of the tail of the skill

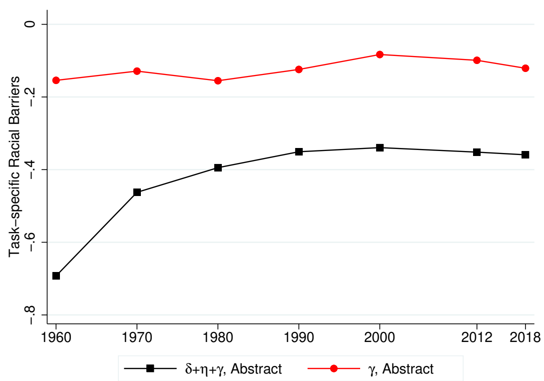
[A15] This is closer to the upper bound of the reasonable range suggested by Chetty et al. (2013). We make this choice because $\varepsilon_t^g$ in our model maps to the elasticity over 10 years.

Figure R15: Task-Specific Racial Barriers for *Abstract* and *Contact* Tasks, Alternate $\psi$'s

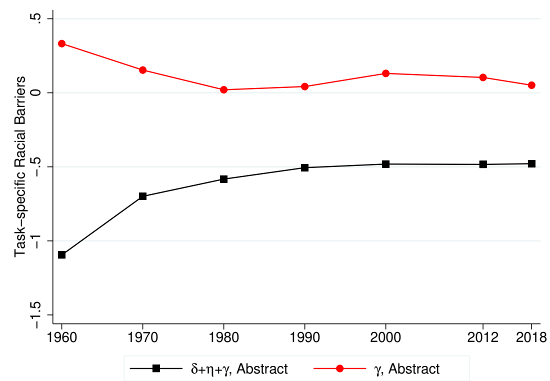



Panel A: $\psi = 3.5$, Contact


Panel B: $\psi = 5.5$, Contact




Panel C: $\psi = 3.5$, Abstract




Panel D: $\psi = 5.5$, Abstract

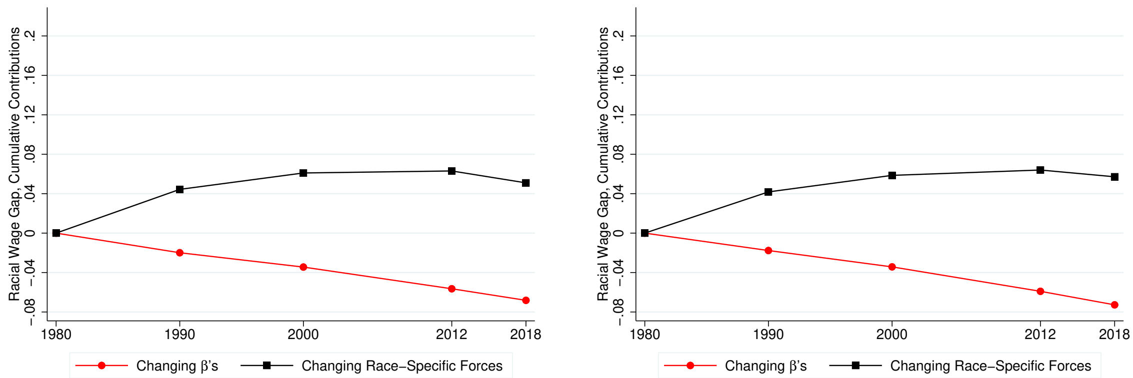
*Notes:* Figure shows our model estimates of the composite racial barrier $(\eta^b_{kt} + \delta^b_{kt} + \gamma^b_{kt})$ and the component that is due to non-pecuniary discrimination $(\gamma^b_{kt})$ for *Contact* tasks (Panels A and B) and *Abstract* tasks (Panels C and D). Panels A and C show estimates under $\psi = 3.5$, while Panels B and D show estimates under $\psi = 5.5$.

distributions. In the baseline specification, we choose $\theta$ to best fit the trends in aggregate task contents and Miceritan task premiums. This yields $\theta = 3.60$. However, one might worry that our results are sensitive to the choice of $\theta$. Indeed, the sensitivity analysis in Appendix I.4 reveals that small changes in the moments can shift the estimate of $\theta$. In this section, we show the paper's main results when we re-estimate the model assuming $\theta = 2.8$ and $\theta = 4.5$.[A16]

First, as before, we examine the robustness of our finding that racial gaps in *Contact* tasks

[A16] Let us comment on the reason behind these choices. Note that the variance of the Frechet distribution goes to $\infty$ as $\theta \to 2$. Thus, we consider the values of $\theta$ near 2 to be unrealistic. We pick $\theta = 2.8$ because this is roughly the mid-point between the theoretical lower bound of 2 and the baseline estimate of 3.6. As for the upper value, we also tried $\theta = 6.0$ but the results are quite similar to the ones with $\theta = 4.5$. Intuitively, beyond a certain level of $\theta$ the tail of the distribution becomes sufficiently thin that raising $\theta$ further matters less at the margin.

Figure R16: Cumulative Contributions to Changes in Racial Wage Gaps Over Time, 1980-2018, Alternate $\psi$'s




Panel A: $\psi = 3.5$ Panel B: $\psi = 5.5$

*Notes:* Figure shows cumulative contributions of race-neutral forces ($\beta_{kt}$'s) and race-specific forces ($\delta^b_{kt}$'s, $\eta^b_{kt}$'s, $\gamma^b_{kt}$'s, and $A^b_t$'s) to the evolution of the racial wage gaps over the 1980 to 2018 period when $\psi$ is set to 3.5 (Panel A) and 5.5 (Panel B).

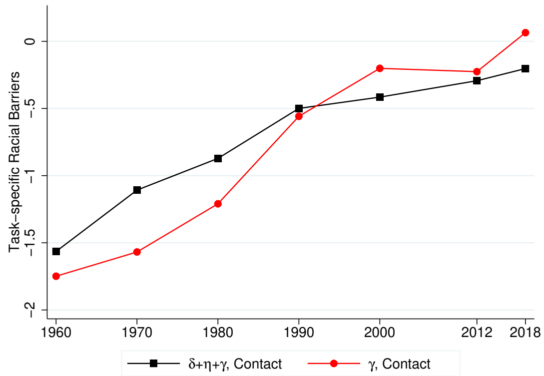
provide a good proxy for direct discrimination. Figure R17 plots the model estimates of the composite racial barrier ($\eta^b_{kt} + \delta^b_{kt} + \gamma^b_{kt}$) and the component that is due to non-pecuniary discrimination ($\gamma^b_{kt}$) for *Contact* tasks (Panels A and B) and *Abstract* tasks (Panels C and D) under the alternative values of $\theta$. Specifically, Panels A and C show the estimates under $\theta = 2.8$, while Panels B and D show the estimates under $\theta = 4.5$. The comparison of Panels A and B shows that regardless of whether we set $\theta$ to 2.8 or 4.5 the racial barrier in *Contact* tasks is driven primarily by non-pecuniary discrimination, both in level and in trend. In contrast, pecuniary barriers $\delta^b_{kt} + \eta^b_{kt}$ explain a large part of the composite racial barrier in *Abstract* tasks, again regardless of the choice of $\theta$.[A17]

Next, we explore the robustness of the finding that the rising *Abstract* task returns post-1980 underlay the stagnation of the racial wage gap post-1980. To this goal, Figure R18 shows the cumulative contributions of changing race-neutral and race-specific forces to the evolution of the racial wage gap under the alternative $\theta$ values, $\theta = 2.8$ (Panel A) and $\theta = 4.5$ (Panel B). The results are largely the same across the two panels, though the contribution of changing task prices is slightly smaller with $\theta = 4.5$ than with $\theta = 2.8$ (6.4 log points versus 8.0 log points over the 1980-2018 period).[A18] Overall, the results point to the robustness of our key model findings to alternative assumptions on $\theta$.

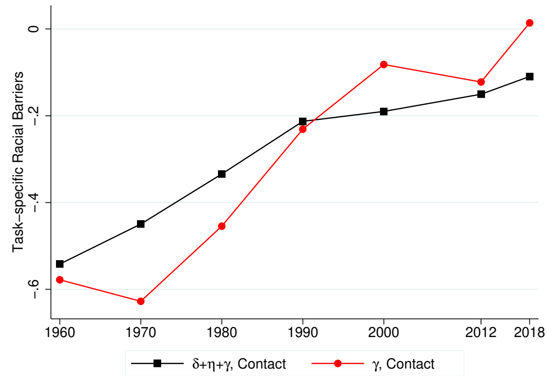
[A17]However, the size of the estimated task-specific racial barriers is much smaller with the higher value of $\theta$. This is largely because a higher $\theta$ (i.e. thinner tail of the skill distribution) implies a higher $\beta_{kt}$'s – both because the mean of the skill distribution falls with $\theta$ and because the thinner tail lowers the Mincerian task premium – and re-scale the race-specific parameters.

[A18]The difference stems primarily from the proportional increase in the estimated $\beta_{kt}$ for *Abstract* being larger when $\theta = 2.8$.

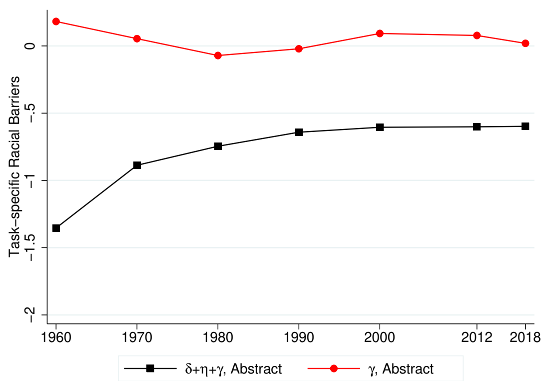
Figure R17: Task-Specific Racial Barriers for *Abstract* and *Contact* Tasks, Alternate $\theta$'s



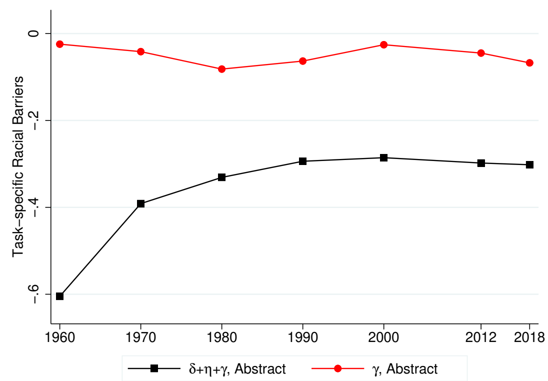

Panel A: $\theta = 2.8$, Contact




Panel B: $\theta = 4.5$, Contact




Panel C: $\theta = 2.8$, Abstract



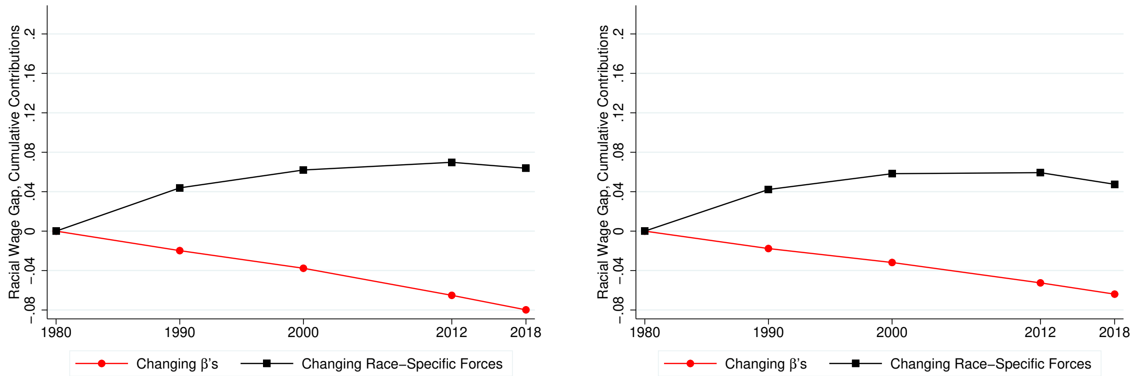

Panel D: $\theta = 4.5$, Abstract

*Notes:* Figure shows our model estimates of the composite racial barrier ($\eta^b_{kt} + \delta^b_{kt} + \gamma^b_{kt}$) and the component that is due to non-pecuniary discrimination ($\gamma^b_{kt}$) for *Contact* tasks (Panels A and B) and *Abstract* tasks (Panels C and D). Panels A and C show estimates under $\theta = 2.8$, while Panels B and D show estimates under $\theta = 4.5$.

# Appendix G Adding Statistical Discrimination to the Model

In this section of the appendix, we augment our base model by incorporating statistical discrimination. If employers do not perfectly observe individual workers' skills, then employers form expectations about a worker's marginal product by using information about the individual's group, giving rise to the possibility of statistical discrimination by group. The statistical discrimination term, which we denote $\pi^g_k(.)$, will endogenously differ by task depending on both group-level gaps in underlying skills, $\eta^g_{kt}$'s, and the noise at which employers observe a worker's skills.

Figure R18: Cumulative Contributions to Changes in Racial Wage Gaps Over Time, 1980-2018, Alternate $\theta$'s




PANEL A: $\theta = 2.8$ PANEL B: $\theta = 4.5$

*Notes:* Figure shows cumulative contributions of race-neutral forces ($\beta_{kt}$'s) and race-specific forces ($\delta^b_{kt}$'s, $\eta^b_{kt}$'s, $\gamma^b_{kt}$'s, and $A^b_t$'s) to the evolution of the racial wage gaps over the 1980 to 2018 period when $\theta$ is set to 2.8 (Panel A) and 4.5 (Panel B).

## Appendix G.1 Modeling Statistical Discrimination

Formally, we incorporate the notion of statistical discrimination into the model by introducing noise to skill measurement. Suppose employers cannot observe a worker's true efficiency, $\eta^g_k + \phi_{ik}$, and instead only observe a noisy skill measure given by

$$s^g_{ik} = (\eta^g_k + \phi_{ik}) + \epsilon_{ik}, \tag{R5}$$

where the noise $\epsilon_{ik}$ is drawn from a normal distribution with mean zero and variance $\sigma^2$ (common to all groups). Employers, however, observe worker's group affiliation and know the underlying distributions of $\eta^g_k + \phi_{ik}$ and $\epsilon_{ik}$. In this environment, employers set the wage of each worker at the worker's expected marginal revenue product conditional on observed skills $(\hat{s}_{i1}, ..., \hat{s}_{ik})$ and the worker's group affiliation, adjusted for direct pecuniary discrimination $\delta^g_{kt}$.[A19]

Specifically, the wage offered in occupation $o$ equals

$$\begin{aligned}\omega^g_{io} &= \omega^{cond,g}_o(\hat{s}_{i1}, ..., \hat{s}_{ik}; \sigma^2) \\ &\equiv A_t + A^g_t + A_o + \sum_K \beta_{kt}\tau_{ok}\left(\phi^e_k(\hat{s}_{ik};\ \beta_{kt}\tau_{ok};\ \sigma^2) + \delta^g_k + \pi'^g_k(\hat{s}_{ik};\ \beta_{kt}\tau_{ok}, \eta^g_k;\ \sigma^2)\right),\end{aligned}$$

[A19]Strictly speaking, the expected marginal revenue product should be conditional on the worker choosing occupation $o$. However, note that workers choose occupations based on observable skills $(\hat{s}_{i1}, ..., \hat{s}_{ik})$ and not based on true efficiencies $(\eta^g_1 + \phi_{i1}, ..., \eta^g_K + \phi_{iK})$, as the wages depend only on the former. Thus, conditional on observed skills and group affiliation, the distribution of $\phi's$ among workers choosing occupation $o$ is the same as the one among all workers in the group. Hence, we can omit the conditioning on occupational choice.

where

$$\phi_k^e(\hat{s}_{ik};\, \beta_{kt}\tau_{ok};\, \sigma^2) = \log E\left[e^{\beta_{kt}\tau_{ok}\phi} \mid s_{ik}^w = \hat{s}_{ik}\right]^{1/\beta_{kt}\tau_{ok}}$$

is the expected efficiency of White workers in task $k$ conditional on observing $\hat{s}_{ik}$, and

$$\pi_k^g(\hat{s}_{ik};\, \beta_{kt}\tau_{ok}, \eta_k^g;\, \sigma^2) = \log E\left[e^{\beta_{kt}\tau_{ok}(\phi+\eta_k^g)} \mid s_{ik}^g = \hat{s}_{ik}\right]^{1/\beta_{kt}\tau_{ok}} - \log E\left[e^{\beta_{kt}\tau_{ok}\phi} \mid s_{ik}^w = \hat{s}_{ik}\right]^{1/\beta_{kt}\tau_{ok}} \tag{R6}$$

is the statistical discrimination coefficient measured relative to White workers. In words, the statistical discrimination coefficient equals the gap in the conditional expected efficiency relative to the base group and will be non-zero if $\eta_k^g$ is non-zero and $\sigma^2$ is positive. Overall, racial wage gaps conditional on identical observed credentials will be a combination of direct and statistical discrimination:

$$\omega_o^{cond,b}(\hat{s}_{i1}, ..., \hat{s}_{ik}; \sigma^2) - \omega_o^{cond,w}(\hat{s}_{i1}, ..., \hat{s}_{ik}; \sigma^2) = \sum_k \beta_{kt}\tau_{ok}\left(\delta_k^g + \pi_k^g(\hat{s}_{ik};\, \beta_{kt}\tau_{ok}, \eta_k^g;\, \sigma^2)\right). \tag{R7}$$

Conceptually, it would be useful to see the statistical discrimination term $\pi_k^g$ as a product of a Bayesian updating process. Before they observe a signal (i.e., the observed skill $s_{gik}$), the employers' prior on the true efficiency of a worker coincides with the true efficiency distribution for the group to which the worker belongs. They thus expect the true skill of a randomly chosen worker to differ by $\eta_k^g$ across groups. However, upon observing the signal $s_{gik}$, they update their prior to reflect this new piece of information. The extent of the updating depends on the reliability of the signal, namely the amount of noise with which employers observe worker skills ($\sigma^2$). If the signal is perfect ($\sigma^2$=0), employers set the wages solely based on the signal and workers are paid exactly their true marginal product (perceived by the employer, i.e., adjusting for $\delta_k^g$):

$$\omega_{io}^g = A_t + A_t^g + A_o + \sum_K \beta_{kt}\tau_{ok}(\phi_{ik} + \delta_k^g + \eta_k^g). \tag{R8}$$

In this case, there will be no statistical discrimination and the racial wage gap conditional on observed skills will only stem from the $\delta_{kt}^b$'s and $A_t^g$'s as in our base model in the paper:

$$\lim_{\sigma^2\to 0} \pi_k^g(\hat{s}_{i1}, ..., \hat{s}_{ik}; \sigma^2) = 0, \quad \forall \hat{s}_{i1}, ..., \hat{s}_{ik}.$$

Conversely, if the signal is completely uninformative ($\sigma^2 \to \infty$), no updating takes place and employers pay workers solely based on their initial priors. In this case, the statistical discrimination term for workers of group $g$ will equal the mean racial skill gap regardless of the observed credentials:

$$\lim_{\sigma^2\to \infty} \pi_k^g(\hat{s}_{i1}, ..., \hat{s}_{ik}; \sigma^2) = \eta_k^g, \quad \forall \hat{s}_{i1}, ..., \hat{s}_{ik}.$$

More generally, when signals are imperfect but not totally uninformative, the expected marginal product conditional on observed skills is something akin to a weighted average of the signal and the prior, where the relative weight on the latter increases with the variance of noise $\sigma^2$. Hence, employers will tend to pay more based on the group mean and less based on observed skills of individual workers in a noisier environment.

Another notable implication of equation (R6) is the following:

**Proposition 3.** *The statistical discrimination term, $\pi_k^g(\hat{s}_{ik};\, \beta_{kt}\tau_{ok}, \eta_k^g;\, \sigma^2)$, tends to zero as $\eta_k^g \to 0$.*

*Proof.* This is immediate from (R5) and (R6). □

This proposition says that there cannot be any statistical discrimination in tasks where there is no mean gap in skills between Black and White men. When skills are noisily observed by employers, employers put weight on their prior expected difference in skills between workers from different groups when setting individual wages. As racial skill gaps associated with a task tend to zero, statistical discrimination in that task will therefore also tend to zero.

## Appendix G.2 Implications of Statistical Discrimination for our Paper's Key Results

Adding statistical discrimination to our model would not change any of the paper's key results. Intuitively, the statistical discrimination term $\pi_{kt}^b(.)$ is just another pecuniary racial task-barrier like pecuniary discrimination $\delta_{kt}^b$.[A20] Thus, even if we do not model statistical discrimination explicitly, the pecuniary discrimination term $\delta_{kt}^b$ will capture the effects of statistical discrimination when we estimate the model. Unless we want to assess how much of $\delta_{kt}^b$ is due to statistical discrimination – which is in any case not possible without an assumption on the amount of noise $\sigma^2$ – we do not need to model statistical discrimination explicitly.

Hence, the only place where statistical discrimination would change the quantitative results in the paper is for the results discussed in Section 8, where we use data from the NLSY to decompose how much of the racial task barriers in *Contact* and *Abstract* tasks are due to racial skill gaps versus direct discrimination. First, we note that the addition of statistical discrimination will not impact our conclusions regarding *Contact* tasks. Recall that the data from the NLSY shows that there is no racial skill gap in the skills associated with *Contact* tasks. As seen from the proposition above, when there is no skill racial skill gap ($\eta_{kt}^b$) in a task, statistical discrimination in that task will be zero by definition.[A21]

Second, unlike for *Contact* tasks, a part of the labor market discrimination in *Abstract* tasks might be due to statistical discrimination. The data from the NLSY shows a large racial skill gap in the skills associated with *Abstract* tasks. This implies that a part of the pecuniary Beckerian discrimination term $\delta_{kt}^b$ that we isolate could actually reflect statistical discrimination. Given that the statistical discrimination arises from the racial gap in *Abstract* skills, we might be underestimating the effects of racial skill gaps in *Abstract* tasks when we do not model statistical discrimination explicitly. However, our finding that most of the racial task barrier for *Abstract* tasks is due to racial skill gaps would remain unchanged.

[A20] Strictly speaking, $\pi_{kt}^b(.)$ can differ at the occupation level, while $\delta_{kt}^b$ differs only at the task level. But this additional variation at the occupation level is quantitatively unimportant under reasonable parameterizations.

[A21] In the model of statistical discrimination we considered above, we allowed the mean of the worker skills to vary by race but assumed the variance of the noise $\sigma^2$ to be the same across groups. Allowing the variance of the noise to differ by race (in the spirit of Aigner and Cain (1977)) could introduce a racial wedge in the returns to observed skills even when the mean worker skills are the same across race groups. However, it would still not change our key conclusion regarding *Contact* tasks since we estimate the pecuniary discrimination term (which will capture the effect of statistical discrimination) for the task to be almost zero.

To summarize, the addition of statistical discrimination to our base model in the paper would add a lot more notation without changing any of our key findings in the paper. It would just add another term to the pecuniary task-specific racial barriers. Further, the pecuniary task-specific racial barriers are not important for explaining the racial gap in *Contact* tasks, so adding statistical discrimination would not alter our conclusions that the racial gap in *Contact* tasks is a good proxy for direct measures of non-pecuniary discrimination in the economy.

# Appendix H Proposition Proofs and Additional Estimation Details

This section of the appendix provides proofs for the propositions in Section 2.7 and derivations of other analytical results stated in the section.

## Appendix H.1 Various Derivations and Propositions Proofs

### Appendix H.1.1 Employment Share of Occupations

We first derive the expression for the employment share of each occupation. Recall that, conditional on working, workers with skill draws $\vec{\phi}$ self-select into the occupation $o$ that maximizes utility given by the sum of log earnings $\omega^g_{ot}(\vec{\phi})$, the disutility due to non-pecuniary discrimination $\gamma^g_{ot}$, and their non-pecuniary idiosyncratic preference for occupations $\log \nu_{io}$. Recall furthermore that the occupational preferences $\nu_{io}$ follow a Frechet distribution with scale 1 and shape $\psi$. As in the main text, define $\hat{u}^g_{ot}(\vec{\phi}) = A_t + A^g_t + A_o + \sum_k \beta_{kt}\tau_{ok}\left((\delta^g_{kt} + \eta^g_{kt} + \gamma^g_{kt}) + \phi_{ik}\right)$ to be the non-idiosyncratic component of the utility that a worker of group $g$ with skill draws $\vec{\phi}$ would attain in occupation $o$. Letting $f_\nu$ and $F_\nu$ respectively denote the pdf and cdf of the distribution, the fraction of group $g$ workers who choose occupation $o$ conditional on working and having skill draws $\vec{\phi} = \{\phi_1, ..., \phi_K\}$ is given by:

$$\begin{aligned}
\rho^g_{ot}(\vec{\phi}) &= \Pr\left[\exp\{\hat{u}^g_{ot}(\vec{\phi})\}\nu_o > \exp\{\hat{u}^g_{o't}(\vec{\phi})\}\nu_{o'},\ \forall o' \neq o, H\right] \\
&= \int_0^\infty f_\nu(\nu)\, \Pi_{o'\neq o,H} F_\nu\left(\exp\left\{\hat{u}^g_{ot}(\vec{\phi}) - \hat{u}^g_{o't}(\vec{\phi})\right\}\nu\right) d\nu \\
&= \int_0^\infty f_\nu\left(\textstyle\sum_{o'\neq H} \exp\left\{\psi\hat{u}^g_{o't}(\vec{\phi}) - \psi\hat{u}^g_{ot}(\vec{\phi})\right\}\nu\right) d\nu \\
&= \frac{\exp\{\psi\hat{u}^g_{ot}(\vec{\phi})\}}{\sum_{o'\neq H}\exp\{\psi\hat{u}^g_{o't}(\vec{\phi})\}}.
\end{aligned}$$

The labor market participation rate for group $g$ workers with skill draws $\vec{\phi}$, $L^g_t(\vec{\phi})$, is derived similarly.

### Appendix H.1.2 Proofs of Propositions 1-2

We next provide proofs for the propositions in the text. First, note that the total derivative of the log employment share for occupation $o \neq H$ is given by

$$d \log \rho^g_{ot}(\vec{\phi}) = \psi \left[ d\hat{u}^g_{ot}(\vec{\phi}) - \sum_{o' \neq H} \rho^g_{o't}(\vec{\phi}) d\hat{u}^g_{o't}(\vec{\phi}) \right].$$

Thus, the total derivative of the mean log wage $\overline{\omega}^g_t(\vec{\phi}) = \sum_{o \neq H} \rho^g_{ot}(\vec{\phi}) \omega^g_{ot}(\vec{\phi})$ is given by

$$\begin{aligned} d\overline{\omega}^g_t(\vec{\phi}) &= \sum_{o \neq H} \rho^g_{ot}(\vec{\phi}) d\omega^g_{ot}(\vec{\phi}) + \sum_{o \neq H} \rho^g_{ot}(\vec{\phi}) \omega^g_{ot}(\vec{\phi}) d \log \rho^g_{ot}(\vec{\phi}) \\ &= \sum_{o \neq H} \rho^g_{ot}(\vec{\phi}) d\omega^g_{ot}(\vec{\phi}) + \psi \left[ \sum_{o \neq H} \rho^g_{ot}(\vec{\phi}) \omega^g_{ot}(\vec{\phi}) d\hat{u}^g_{ot}(\vec{\phi}) - \overline{\omega}^g_t(\vec{\phi}) \sum_{o' \neq H} \rho^g_{o't}(\vec{\phi}) d\hat{u}^g_{o't}(\vec{\phi}) \right] \\ &= \sum_{o \neq H} \rho^g_{ot}(\vec{\phi}) d\omega^g_{ot}(\vec{\phi}) + \psi \left[ \sum_{o \neq H} \rho^g_{ot}(\vec{\phi}) \left( \omega^g_{ot}(\vec{\phi}) - \overline{\omega}^g_t(\vec{\phi}) \right) d\hat{u}^g_{ot}(\vec{\phi}) \right]. \end{aligned}$$

The expression is intuitive. The first term is the direct effect of a change in the log wage in each occupation $o \neq H$. The second term is the indirect effect through sorting. If occupation $o$ offers a higher wage than the average wage $\overline{\omega}^g_t(\vec{\phi})$ given skill draws $\vec{\phi}$, the increase in the wage of the occupation – which attracts more workers to occupation $o$ – will tend to increase the average wage for workers with skill $\vec{\phi}$ above and beyond the direct effect.

The total derivative of potential wage $\omega^g_{ot}(\vec{\phi})$ in each occupation is given by

$$d\omega^g_{ot}(\vec{\phi}) = dA_t + dA^g_t + dA_o + \sum_k (d\beta_{kt}\tau_{ok} + \beta_{kt} d\tau_{ok})(\phi_k + \eta^g_{kt} + \delta^g_{kt}) + \sum_k \beta_{kt}\tau_{ok} d(\eta^g_{kt} + \delta^g_{kt}),$$

while the total derivative of the non-idiosyncratic part of utility $\hat{u}^g_{ot}(\vec{\phi})$ in each occupation is given by

$$d\hat{u}^g_{ot}(\vec{\phi}) = d\omega^g_{ot}(\vec{\phi}) + \sum_k (d\beta_{kt}\tau_{ok} + \beta_{kt} d\tau_{ok})\gamma^g_{kt} + \sum_k \beta_{kt}\tau_{ok} d\gamma^g_{kt}.$$

Substituting these expressions into the total derivatives above will yield the results in Propositions 2. To prove Proposition 1, note the total derivative of the average task content $\overline{\tau}^g_{kt}(\vec{\phi})$ is given by

$$d\overline{\tau}^g_{kt}(\vec{\phi}) = \sum_{o \neq H} \rho^g_{ot}(\vec{\phi}) d\tau_{ok} + \psi \left[ \sum_{o \neq H} \rho^g_{ot}(\vec{\phi}) \left( \tau_{ok} - \overline{\tau}^g_{kt}(\vec{\phi}) \right) d\hat{u}^g_{ot}(\vec{\phi}) \right],$$

and proceed similarly as above. Last, analogously to the occupational labor shares, the total derivative of the labor market participation rate $L^g_t(\vec{\phi})$ – which we discuss next – is given by

$$d \log L^g_t(\vec{\phi}) = -\psi(1 - L^g_t(\vec{\phi})) \left[ d\hat{u}_{gHt}(\vec{\phi}) - \sum_{o' \neq H} \rho^g_{o't}(\vec{\phi}) d\hat{u}^g_{o't}(\vec{\phi}) \right].$$

## Appendix H.2 Additional Comparative statics

This section presents additional comparative static results extending Section 2.7.

### Appendix H.2.1 Labor Market Participation and Labor Supply Elasticity

First we present comparative statics on the labor market participation rate and thus derive the labor supply elasticity. The labor supply elasticity is used in model estimation to pin down the Frechet shape parameter $\psi$ for the occupational preference distribution.

**Proposition 4.** *Race-neutral and race-specific forces affect the conditional labor market participation rate $L_t^g(\vec{\phi})$ as follows:*

$$\frac{dL_t^g(\vec{\phi})}{d\beta_{kt}} = -\psi L_t^g(\vec{\phi})(1 - L_t^g(\vec{\phi}))\left(\tau_{Hk} - \overline{\tau}_{kt}^g(\vec{\phi})\right)(\phi_k + \eta_{kt}^g + \delta_{kt}^g + \gamma_{kt}^g),$$

$$\frac{dL_t^g(\vec{\phi})}{d(\eta_{kt}^g + \delta_{kt}^g + \gamma_{kt}^g)} = -\psi L_t^g(\vec{\phi})(1 - L_t^g(\vec{\phi}))\left(\tau_{Hk} - \overline{\tau}_{kt}^g(\vec{\phi})\right)\beta_{kt}.$$

Note the sign of both derivatives depends on whether the task content of home sector, $\tau_{Hk}$, is higher than the task content in the average occupations where the workers with given skill draws are employed. For example, if the task content for the home sector is higher than $\overline{\tau}_{kt}^g(\vec{\phi})$, then a rise in the task price will induce some workers to exit the labor market if they possess skills for the task.

**Proposition 5.** *The scale parameter for home sector preference, $A_{gH}$, affects the conditional labor market participation rate $L_t^g(\vec{\phi})$ as follows:*

$$\frac{dL_t^g(\vec{\phi})}{dA_{gH}} = -\psi L_t^g(\vec{\phi})(1 - L_t^g(\vec{\phi})) \leq 0.$$

*Furthermore, $A_{gH}(\vec{\phi})$ has no impact on conditional employment shares $\rho_{ot}^g(\vec{\phi})$ for $o = 1, ..., O$ or on the conditional mean log wages $\overline{\omega}(\vec{\phi})$.*

**Corollary 2.** *The labor supply elasticity $\varepsilon_t^g$ is given by*

$$\varepsilon_t^g \equiv -\frac{1}{\overline{L}_{gt}} \int \frac{dL_t^g(\vec{\phi})}{dA_{gH}} dF(\vec{\phi}) = \psi \int \frac{L_t^g(\vec{\phi})(1 - L_t^g(\vec{\phi}))}{\overline{L}_{gt}} dF(\vec{\phi}).$$

The first equality holds because a symmetric increase in log wages of all occupations is isomorphic to a decrease in $A_{gH}$. Note, rearranging, we can write

$$\varepsilon_t^g = \psi\,(1 - L_t^g) - \psi \int \frac{(L_t^g(\vec{\phi}) - \overline{L}_{gt})^2}{\overline{L}_{gt}} dF(\vec{\phi}).$$

The second term is quantitatively small under reasonable parameterizations. Thus, the labor supply elasticity is just below $\psi$ times the home sector share. We use this fact to set the value of $\psi$.

### Appendix H.2.2 Derivatives of Aggregate Racial Wage Gap

In Corollary 1 of the main paper, we presented an approximate result for comparative statics on aggregate wages $\overline{\omega}_t^{agg,g}$, which ignored both intensive and extensive sorting (i.e., sorting across occupations and sorting into and out of labor force). Here, we give an exact result reflecting the sorting effects:

**Proposition 6.** *Race-neutral and race-specific forces affect the aggregate wage $\overline{\omega}_t^{agg,g}$ for workers of group $g$ as follows:*

$$\frac{d\overline{\omega}_t^{agg,g}}{d\beta_{kt}} = \int \left[\frac{d\overline{\omega}_t^g(\vec{\phi})}{d\beta_{kt}} + (\overline{\omega}(\vec{\phi}) - \overline{\omega}_t^{agg,g})\frac{d\ln L_t^g(\vec{\phi})}{d\beta_{kt}}\right] \frac{L_t^g(\vec{\phi})}{\overline{L}_{gt}} dF(\vec{\phi})$$

$$\frac{d\overline{\omega}_t^{agg,g}}{d(\eta_{kt}^g + \delta_{kt}^g)} = \int \left[\frac{d\overline{\omega}_t^g(\vec{\phi})}{d(\eta_{kt}^g + \delta_{kt}^g)} + (\overline{\omega}(\vec{\phi}) - \overline{\omega}_t^{agg,g})\frac{d\ln L_t^g(\vec{\phi})}{d(\eta_{kt}^g + \delta_{kt}^g)}\right] \frac{L_t^g(\vec{\phi})}{\overline{L}_{gt}} dF(\vec{\phi})$$

$$\frac{d\overline{\omega}_t^{agg,g}}{d\gamma_{kt}^g} = \int \left[\frac{d\overline{\omega}_t^g(\vec{\phi})}{d\gamma_{kt}^g} + (\overline{\omega}(\vec{\phi}) - \overline{\omega}_t^{agg,g})\frac{d\ln L_t^g(\vec{\phi})}{d\gamma_{kt}^g}\right] \frac{L_t^g(\vec{\phi})}{\overline{L}_{gt}} dF(\vec{\phi})$$

The first term inside the square brackets captures the direct effect of changing returns within occupations, as well as the intensive margin adjustments of sorting across occupations (c.f., Proposition 2). The second term, on the other hand, captures the extensive margin adjustment in labor market participation; increased participation rates ($d\ln L_t^g > 0$) among workers who would on average earn a higher wage than the current aggregate wage (i.e., workers with $\overline{\omega}(\vec{\phi}) > \overline{\omega}_t^{agg,g}$) tend to push up the aggregate wage. Naturally, the derivatives of the racial wage gap $\overline{\omega}^{gap} \equiv \overline{\omega}_t^{agg,b} - \overline{\omega}_t^{agg,w}$ are given by the difference of the respective derivatives for $g = b$ and $g = w$, e.g., $\frac{d\overline{\omega}^{gap}}{d\beta_{kt}} = \frac{d\overline{\omega}_t^{agg,b}}{d\beta_{kt}} - \frac{d\overline{\omega}_t^{agg,w}}{d\beta_{kt}}$.

# Appendix I Estimation Details

Section 4 of the text discusses the estimation procedure in detail. This section provides some additional details not mentioned in the text.

## Appendix I.1 Construction of $\tau_{ok}$'s for the Model Estimation

As discussed in the text, we use the O*NET and DOT data to pin-down the task content of occupations $T_{ok} = (\tau_{o1}, ..., \tau_{oK}) \in \mathcal{R}_+^K$ of occupations. However, we cannot directly use the z-scores of task content we defined earlier since $\tau_{o1}, ..., \tau_{oK}$ have to be non-negative in the model. Also, in the model estimation, we follow the procedure in Hsieh et al. (2019) by aggregating occupations to 66 broad occupation categories, where the broad occupation categories we use come from the Census occupation sub-headings in 1990.

We therefore construct $\tau_{o1}, ..., \tau_{oK}$ for the model estimation from the z-scores of task content in two steps. First, in each Census year, we aggregate the z-scores of task content defined over the narrower 3-digit occupational code level to the 66 broad occupation categories by taking the average of task contents across all 3-digit occupations within each broad occupational category weighted by employment shares.[A22] Second, we apply an affine transformation to the aggregated z-scores of task content so that all the task requirements used in the model lie within the unit interval [0, 1]. Specifically, for each task $k$, the affine transformation $T$ is given by

$$T\left(\tau_{ok}\right)=\frac{\tau_{ok}-\tau_k^{min}}{\tau_k^{max}-\tau_k^{min}}$$

where $\tau_k^{min}=\min_o \tau_{ok}$ and $\tau_k^{max}=\max_o \tau_{ok}$ The two assumptions underlying the transformation are: (i) the z-scores map linearly to the requirement for each task and (ii) the occupation with the lowest requirements for task $k$ requires zero amount of the task. The change of scaling to a unit interval is otherwise innocuous given that the $\beta_{kt}$'s scale the task requirements accordingly.

In fact, while we assume $\tau_{ok}$'s to be constant over time, our model can capture phenomena such as *Abstract* task requirements increasing relative to *Routine* task requirements within all occupations, an empirical fact observed by several recent papers (see, for example, Cavounidis et al. (2021)). Since $\beta_{kt}$'s scale $\tau_{kt}$'s, a uniform proportional increase within all occupations in the requirement for one task is isomorphic to an increase in the $\beta_{kt}$ for the task. Thus, any systemic change to the task structure of the economy will be captured in the model as changes in $\beta_{kt}$'s over time, whose effects on the aggregate racial wage gap we estimate through the lens of the model.

## Appendix I.2 Weights in Model Estimation

We estimate the race-neutral parameter vector $\Theta^w=(\{A_t\},\{A_o\},\{A_{Ht}\},\{\beta_{kt}\},\theta)$, as discussed in Section 4, through the minimum distance estimation. The set of moments we target are: (i) the average log income of White men in each occupation in each year; (ii) log of employment share of White men in each occupation in each year; (iii) log of the non-employment rate of White men in each year; (iv) the empirical price of each task for White men in each year (shown in Figure 3 Panel A); and (v) the aggregate content of each task for White men in each year. We weight moments to adjust for scaling differences and to fit task-related moments (iv) and (v) more closely than occupation-level moments. Specifically, we weight the occupation-level moments (i) and (ii) by $(N_O N_T)^{-1}$ where $N_O=66$ is the number of occupations and $N_T=7$ is the number of time periods in the estimation. (The division by $N_T$ is meant to account for the fact that the occupation-level parameters $A_o$ are time-invariant while we target the occupation-level moments in each period.) Furthermore, we weight the Mincerian task premiums $5^2$ times more than the aggregate task contents. This amounts to re-scaling Micerian task premiums by a factor of 5. This is to roughly adjust for scaling differences and to match the rising *Abstract* task premium post-1980 – which is the key driving force – closely. The resulting fit can be seen in Appendix F.

As noted in the main text, the weights in the second stage of the estimation (where we

[A22] Since we perform the aggregation year-by-year, the task requirements $\tau_{o1},...,\tau_{oK}$ we use in the model estimation vary slightly across years due to the differences in the weights used in the aggregation over time. This is inevitable to ensure consistency between the task-related moments (e.g., aggregate task content gaps) we calculate in the data and the model, since the data regressions are based on the task requirements at the 3-digit occupational code level. However, the extent of changes in the aggregated $\tau_{kt}$'s over time is small and its estimated contribution to the evolution of the racial wage gap is virtually zero.

estimate race-specific parameters $\Theta_t^b$) do not matter so long as they are strictly positive, since we match the moments perfectly.

## Appendix I.3 Optimization Algorithm

As explained in Section 4, we estimate parameters with the minimum distance estimator. The parameter search uses a trust-region algorithm for non-linear optimization.[A23] Before starting the optimization, we draw task-specific skills for $12^4 \approx 20,000$ workers. Then, for each set of parameters we evaluate in the optimization process, we calculate the labor share of each occupation and wages earned by workers in the occupations based on these skill draws. We then compute the values of the targeted moments in the model and compute the distance from the data targets as outlined in Section 4. We search over the parameters to minimize the weighted sum of the distance.

## Appendix I.4 Sensitivity Analysis

Andrews et al. (2017) proposes a local measure of the *sensitivity* of parameter estimates to the data moments. The sensitivity analysis increases the transparency of structural estimates by clarifying which parameters are sensitive to which moments and to what extent.

First, we consider the sensitivity of estimates of race-neutral parameters $\Theta^w$. Let $G_w^w$ denote the Jacobian of the moment function for Whites, $m^w(\Theta^w)$, at the true parameter set $\Theta_0^w$. The *sensitivity* matrix $\Lambda^w$ of race-neutral parameter estimates is given by

$$\Lambda^w = -\left(G_w^{w\prime} W^w G_w^w\right)^{-1} G_w^{w\prime} W^w. \tag{R9}$$

The sensitivity matrix $\Lambda^w$ is a local approximation to the mapping from moments to estimated parameters. Specifically, the $ij$-th entry of $\Lambda^w$ shows how much the estimate of the $i$-th parameter in $\Theta^w$ moves when we change the $j$-th data moment in $\hat{m}^w$.

We can define the sensitivity of estimated race-specific parameters similarly. In each period $t$, let $G_{t,w}^w$ and $G_{t,b}^w$ denote the derivatives of the moment function for the Black-White gaps, $m_t^b(\Theta^w, \Theta_t^b)$, with respect to the race-neutral and race-specific parameter sets $\Theta^w$ and $\Theta_t^b$, respectively, again evaluated at the true parameter values $\Theta_0^w$ and $\Theta_{t,0}^b$. Then, the sensitivity of estimated race-specific parameters to data moments on racial gaps, $\hat{m}_t^b$, is given by

$$\Lambda_{t,b}^b = -\left(G_{t,b}^{b\prime} W_t^b G_{t,b}^b\right)^{-1} G_{t,b}^{b\prime} W_t^b, \tag{R10}$$

while the sensitivity to data moments for White men, $\hat{m}^w$, is given by

$$\Lambda_{t,w}^b = \Lambda_{t,b}^b \left(-G_{t,w}^b \Lambda^w\right). \tag{R11}$$

The latter is intuitive. Local changes in $\hat{m}^w$ alters the estimated race-neutral parameters by $\Lambda^w$, which in turn impacts the racial gap moments $m_t^b(\Theta^w, \Theta_t^b)$ in the model by $G_{t,w}^b$. This affects the residual in the second stage $\left(\hat{m}_t^b - m_t^b(\Theta^w, \Theta_t^b)\right)$ by $-G_{t,w}^b \Lambda^w$, to which the estimates of race-specific parameters respond by $\Lambda_{t,b}^b$.

[A23] Specifically, I use the MATLAB solver *lsqnonlin* with the 'trust-region-reflective' algorithm.

Consistent estimators of the sensitivity matrices, denoted with $\hat{\Lambda}^w_w$, $\hat{\Lambda}^b_{t,b}$, and $\hat{\Lambda}^b_{t,w}$, are obtained using the Jacobians $\hat{G}^w_w$, $\hat{G}^b_{t,b}$, and $\hat{G}^b_{t,w}$ evaluated at the estimated parameter values $\hat{\Theta}^w$ and $\hat{\Theta}^b_t$ (rather than at the true parameter values $\Theta^w_0$ and $\Theta^b_{t,0}$). See Andrews et al. (2017) for the derivations of these sensitivity matrices and the required regularity conditions. Below, I present selected entries of the sensitivity matrices to highlight the intuition behind our identification strategy.

#### Appendix I.4.1 Sensitivity of Estimated Race-Neutral Paramete

First, we analyze the sensitivity of estimated race-neutral parameters $\hat{\Theta}^w$. We estimate $\beta_{kt}$ for each task in each period, $A_o$ for each occupation, and the time-invariant shape parameter $\theta$ for skill distributions jointly from the aggregate task contents and Micerian task premiums in each period as well as various occupational moments, as we discuss in Section 4. The GMM estimating race-neutral parameters is clearly over-identified. In particular, we allow only one set of parameters – the $\beta_{kt}$'s – to vary over time, whereas two sets of moments we target – both aggregate task contents and empirical task premiums – evolve over time. The challenge for the model is to match both of these trends at the same time.

The sensitivity analysis in this section serves three purposes. First, we show that an increase in either the aggregate task content or task premium we target in a given year will increase the estimated task price $\beta_{kt}$ in the year relative to $\beta_{kt}$'s in other years. This is fairly intuitive. Second, to shed light on the mechanics of the model estimation, we look at how changes in these task moments impact the estimates of $A_o$'s and the average level of $\beta_{kt}$. We will show that the relative trends of task contents versus task premiums determine whether we explain, for instance, a high aggregate task content with a high task price $\beta_{kt}$ or with high $A_o$'s in the occupations intensive in the task. Last, in the main text, we claimed that the relative trends in aggregate task contents and Mincerian task premiums help identify the shape parameter $\theta$ for the skill distributions. We verify the logic outlined in the text.

In addressing the first two of the three objectives, we explore the sensitivity matrix fixing $\theta$ at its estimated value. In general, changes in $\theta$ naturally induce re-scaling of the $\beta$'s as (i) the mean of the skill distribution changes and (ii) the tail of the skill distribution changes, altering the level of Micerian task premiums. Holding the $\theta$ fixed makes the sensitivity matrix easier to interpret, as it keeps the scaling of parameters the same. We will later discuss the sensitivity of $\theta$ to the moments.

Tables R7 and R8 show selected entries from the sensitivity matrix $\Lambda^w$. Specifically, Table R7 presents the sensitivity of selected race-neutral parameters to aggregate task contents of *Contact* and *Abstract* tasks, while Table R8 presents the sensitivity of those parameters to the Micerian premiums on *Contact* and *Abstract* tasks. In both tables, we present transformations of the race-neutral parameters $\beta_{kt}$ and $A_o$ – defined below – for ease of interpretation. First, we define $\bar{\beta}_k$ to be the average of $\beta_{kt}$ across all periods $t$ and look at the deviation of the $\beta_{kt}$ in each period relative to the average $\bar{\beta}_k$. The estimate (column 1) and the sensitivity (columns 2-15) of $\beta_{kt} - \bar{\beta}_k$ for *Contact* and *Abstract* tasks are presented in the first 14 rows. Second, we characterize estimated $A_o$'s – a 66-dimensional object – by the average slope along each task dimension, $a_k$. Specifically, we define $a_k$ to be the coefficient on each $\tau_{ok}$ in the regression of the occupation constants $A_o$ on all task requirements:[A24]

$$A_o = \bar{a} + \sum_k a_k \tau_{ok} + \epsilon_o.$$

As shown in the first column of each table, the estimates of $a_k$ are generally negative, which means that the marginal revenue product of a worker with zero skills is decreasing in the task requirement $\tau_{ok}$.[A25] This makes sense; a worker with no *Abstract* skills is likely to have a negative marginal product in *Abstract*-intensive occupations such as doctors and lawyers. Finally, in the last four rows of the table (columns 2-15), we analyze the sensitivity of the estimated $\bar{\beta_{kt}}$ and $a_k$ to the moments, again holding $\theta$ fixed.

We make two key observations. First, we focus on the diagonal entries starting the top-left cell and observe that both higher aggregate task content and higher Mincerian task premium for a task in a given year will increase the estimated $\beta_{kt}$ in the task and the year relative to the average $\bar{\beta}_k$, though the sensitivity is higher with changing task premiums. For example, increasing the *Contact* task content by 0.1 standard deviations in 1960 will increase the estimated $\beta_{Contact,t} - \bar{\beta}_{Contact}$ by $0.1 \times 0.06 = 0.006$. This is fairly intuitive, especially given that $\beta_{kt}$'s are the only time-variant parameters.

Second, however, the sensitivity of $\bar{\beta_{kt}}$ and $a_k$ differs markedly depending on whether we vary the task content or task premiums. In particular, higher task content will lower $\bar{\beta}_k$ and increase $a_k$ for the task, whereas a higher task premium will increase $\bar{\beta}_k$ and reduce $a_k$ for the task. This is because the Mincerian task premium is more responsive to $\bar{\beta}_k$ than to $a_k$ for a change that induces the same response in the aggregate task content. Intuitively, the effect of a higher $\beta_{kt}$ is especially strong for workers with high task-specific skill $\phi_{ik}$, who tend to be in occupations with high requirements for the task, so it increases the Mincerian task return a lot; $a_k$, on the other hand, impacts everyone equally conditional on occupational choice. Thus, the model fits a higher task premium with a higher $\bar{\beta}_k$, combined with a lower $a_k$ to keep the aggregate task content unchanged. Conversely, the model fits a higher task content with a higher $a_k$ rather than with a higher $\bar{\beta}_k$ so as to prevent the task premium from rising.

So far, we have analyzed the sensitivity of race-neutral parameters holding $\theta$ fixed. Next, we consider the sensitivity of the estimated $\theta$ to the moments. Recall that in the main text we claimed the relative changes in task returns versus task contents give information about the thickness of the tail of the distribution and help us estimate the shape parameter $\theta$. As we saw above, for a given $\theta$, raising $\beta_{kt}$ naturally increases both aggregate task content and Mincerian task premium in the task. But, holding $\theta$ fixed, it is generally not possible to fit *both* moments simultaneously just by varying $\beta_{kt}$'s. Nonetheless, we claimed, we may hope to fit both moments more closely by varying $\theta$, as this parameter controls the relative responsiveness of task premiums and task contents to $\beta_{kt}$. In this last analysis, we shall substantiate this claim.

Table R9 presents the sensitivity of the estimated $\theta$ with respect to aggregate task contents

[A24] We weight the regression using the empirical employment share of each occupation in 1990.

[A25] A more negative $a_k$ implies that higher skill is needed for a worker to have a positive task return. Note

$$\omega^w_{iot} = A_t + A_o + \sum_K \beta_{kt}\tau_{ok}\phi_{ik} = A_t + \bar{a} + \epsilon_o + \sum_K \beta_{kt}\tau_{ok}\left(\phi_{ik} - (-a_k/\beta_{kt})\right).$$

So, the skill $\phi_{ik}$ must exceed $(-a_k/\beta_{kt})$ for the worker to have a positive task return.

(Panel A) and Mincerian task premiums (Panel B), respectively. The table shows that $\theta$ is most responsive to *Abstract* task contents as well as *Contact* and *Abstract* task premiums. However, the direction of the change in $\theta$ differs by year. For example, an increase in *Abstract* task premium in 2000, 2012 and 2018 lowers $\theta$, while a rise in the task premium in earlier years increases $\theta$, with the sensitivity most positive in 1960 and most negative 2018.

The difference in the direction of the change stems from whether the change to a moment in a particular year increases or decreases the overall change in the moment over the 1960-2018 period. For example, given that *Abstract* task premium is increasing over time, an increase in *Abstract* task premium in the 2000s maps to a larger overall change in the task premium over the 1960-2018 period. Now, recall that $\theta$ controls the thickness of the tail of the skill distribution. In particular, a lower $\theta$ makes the tail of the skill distribution thicker and hence makes the task premiums more responsive to a rise in $\beta_{kt}$'s relative to aggregate task contents. Fitting the larger change in *Abstract* task premium – relative to the aggregate task content – therefore requires a lower $\theta$ (more responsive task premiums relative to task contents). Conversely, an increase in *Abstract* task premium in the earlier years maps to a smaller overall change in the task premium over the 1960-2018 period. This implies a larger $\theta$ (less responsive task premiums relative to task contents). A similar logic applies to the changes in *Contact* task premium.

Observe also that changes in *Abstract* task contents have the opposite effects from changes in *Abstract* task premiums. In particular, an increase in *Abstract* task content in 2000, 2012 and 2018 increases $\theta$, while a rise in the task premium in earlier years reduces $\theta$, with the sensitivity most positive in 1960 and most negative 2018. This is natural since what matters is how *Abstract* task premium changes *relative to aggregate Abstract task content*. For example, an increase in *Abstract* task contents in 2000, 2012, and 2018 maps to there being less increase in *Abstract* task premium relative to *Abstract* task content, which requires a higher $\theta$ to fit.[A26]

Overall, the analysis verifies the claim made in the main text that the relative changes in task returns versus task contents give information about the thickness of the tail of the distribution. Before ending this section, we note that the parameter estimates do not appear to be overly sensitive to the moments when we are holding $\theta$ fixed, while the estimated $\theta$ is far more sensitive to the moments. As noted above, changing $\theta$ in turn will require rescaling of all parameters. Because of this, our sensitivity analysis is less informative when $\theta$ is allowed to vary; there can be a large rescaling of parameters without affecting the qualitative and quantitative conclusions of the paper. Non-linearities – which the sensitivity analysis based on first-order derivatives does not capture – matter more for changes in $\theta$, too. In Appendix F.4, we explore the robustness of our main results to alternative values of $\theta$.

[A26] A similar argument applies to *Contact* task content, except in the non-monotonicity in 1970. Presumably, this is due to the bump in the Mincerian task premium on *Contact* tasks in 1970; a higher *Contact* content in 1970 maps to there being more co-movement between *Contact* task contents and task premium, which imply a higher $\theta$.

Table R7: Sensitivity of Selected Race-Neutral Parameters to Aggregate Task Contents, Fixed $\theta$

| | | Task Content, Contact | | | | | | | Task Content, Abstract | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Est. | 1960 | 1970 | 1980 | 1990 | 2000 | 2012 | 2018 | 1960 | 1970 | 1980 | 1990 | 2000 | 2012 | 2018 |
| $\beta_{Contact,1960} - \bar{\beta}_{Contact}$ | -0.04 | 0.06 | -0.01 | -0.01 | -0.01 | -0.01 | -0.01 | -0.01 | 0.03 | -0.00 | -0.00 | -0.00 | -0.01 | -0.01 | -0.01 |
| $\beta_{Contact,1970} - \bar{\beta}_{Contact}$ | 0.02 | -0.00 | 0.07 | -0.00 | -0.00 | -0.00 | -0.01 | -0.01 | 0.00 | 0.03 | -0.00 | -0.00 | -0.00 | -0.01 | -0.01 |
| $\beta_{Contact,1980} - \bar{\beta}_{Contact}$ | -0.03 | -0.02 | -0.03 | 0.05 | -0.02 | -0.02 | -0.03 | -0.03 | -0.00 | -0.00 | 0.03 | -0.00 | 0.00 | 0.00 | 0.00 |
| $\beta_{Contact,1990} - \bar{\beta}_{Contact}$ | -0.00 | -0.02 | -0.02 | -0.02 | 0.05 | -0.02 | -0.02 | -0.02 | -0.00 | -0.00 | -0.00 | 0.03 | 0.00 | 0.00 | 0.00 |
| $\beta_{Contact,2000} - \bar{\beta}_{Contact}$ | -0.00 | -0.02 | -0.02 | -0.02 | -0.02 | 0.05 | -0.02 | -0.02 | -0.01 | -0.00 | -0.00 | -0.00 | 0.03 | -0.00 | -0.00 |
| $\beta_{Contact,2012} - \bar{\beta}_{Contact}$ | 0.02 | -0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.08 | 0.01 | -0.01 | -0.01 | -0.01 | -0.01 | -0.01 | 0.02 | -0.02 |
| $\beta_{Contact,2018} - \bar{\beta}_{Contact}$ | 0.03 | -0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.08 | -0.01 | -0.01 | -0.01 | -0.01 | -0.01 | -0.02 | 0.03 |
| $\beta_{Abstract,1960} - \bar{\beta}_{Abstract}$ | -0.14 | 0.06 | -0.00 | -0.01 | -0.01 | -0.01 | -0.01 | -0.01 | 0.13 | -0.02 | -0.01 | -0.01 | -0.01 | -0.01 | -0.01 |
| $\beta_{Abstract,1970} - \bar{\beta}_{Abstract}$ | -0.12 | -0.01 | 0.05 | -0.01 | -0.01 | -0.01 | -0.01 | -0.01 | -0.02 | 0.14 | -0.02 | -0.02 | -0.02 | -0.02 | -0.02 |
| $\beta_{Abstract,1980} - \bar{\beta}_{Abstract}$ | -0.09 | -0.00 | 0.00 | 0.06 | -0.00 | -0.00 | -0.00 | -0.00 | -0.02 | -0.02 | 0.13 | -0.02 | -0.02 | -0.02 | -0.03 |
| $\beta_{Abstract,1990} - \bar{\beta}_{Abstract}$ | -0.02 | -0.00 | -0.00 | -0.00 | 0.05 | -0.00 | -0.00 | -0.00 | -0.02 | -0.02 | -0.02 | 0.13 | -0.03 | -0.03 | -0.03 |
| $\beta_{Abstract,2000} - \bar{\beta}_{Abstract}$ | 0.05 | -0.01 | -0.01 | -0.01 | -0.01 | 0.05 | -0.01 | -0.01 | -0.02 | -0.02 | -0.03 | -0.03 | 0.13 | -0.03 | -0.03 |
| $\beta_{Abstract,2012} - \bar{\beta}_{Abstract}$ | 0.15 | -0.02 | -0.02 | -0.02 | -0.02 | -0.01 | 0.04 | -0.01 | -0.03 | -0.02 | -0.02 | -0.02 | -0.02 | 0.14 | -0.02 |
| $\beta_{Abstract,2018} - \bar{\beta}_{Abstract}$ | 0.18 | -0.02 | -0.02 | -0.02 | -0.02 | -0.01 | -0.01 | 0.04 | -0.03 | -0.03 | -0.03 | -0.03 | -0.03 | -0.03 | 0.14 |
| $\bar{\beta}_{Contact}$ | 0.33 | -0.39 | -0.56 | -0.38 | -0.43 | -0.42 | -0.45 | -0.45 | 0.00 | 0.07 | 0.07 | 0.14 | 0.19 | 0.25 | 0.26 |
| $\bar{\beta}_{Abstract}$ | 0.84 | 0.02 | 0.03 | 0.02 | 0.03 | 0.02 | 0.02 | 0.02 | -0.08 | -0.09 | -0.10 | -0.11 | -0.12 | -0.13 | -0.13 |
| $a_{Contact}$ | -0.03 | 0.24 | 0.33 | 0.24 | 0.26 | 0.26 | 0.27 | 0.28 | -0.02 | -0.06 | -0.06 | -0.10 | -0.13 | -0.16 | -0.16 |
| $a_{Abstract}$ | -0.28 | -0.04 | -0.05 | -0.04 | -0.04 | -0.04 | -0.04 | -0.04 | 0.08 | 0.09 | 0.09 | 0.10 | 0.11 | 0.12 | 0.12 |

*Notes:* Table presents the sensitivity of transformations of estimates of selected race-neutral parameters to aggregate task contents for *Contact* and *Abstract* tasks, in the case where we fix $\theta$ at the estimated value. the first column shows the parameter estimate; the remaining columns show the sensitivity. See the text for details.

Table R8: Sensitivity of Selected Race-Neutral Parameters to Mincerian Task Premiums, Fixed $\theta$

| | | Task Premium, Contact | | | | | | | Task Premium, Abstract | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Est. | 1960 | 1970 | 1980 | 1990 | 2000 | 2012 | 2018 | 1960 | 1970 | 1980 | 1990 | 2000 | 2012 | 2018 |
| $\beta_{Contact,1960} - \bar{\beta}_{Contact}$ | -0.04 | 0.94 | -0.16 | -0.16 | -0.16 | -0.16 | -0.16 | -0.16 | -0.17 | 0.02 | 0.02 | 0.03 | 0.03 | 0.03 | 0.03 |
| $\beta_{Contact,1970} - \bar{\beta}_{Contact}$ | 0.02 | -0.17 | 0.94 | -0.17 | -0.17 | -0.17 | -0.17 | -0.17 | 0.01 | -0.16 | 0.01 | 0.02 | 0.02 | 0.02 | 0.02 |
| $\beta_{Contact,1980} - \bar{\beta}_{Contact}$ | -0.03 | -0.16 | -0.14 | 0.98 | -0.15 | -0.16 | -0.16 | -0.16 | 0.03 | 0.04 | -0.16 | 0.03 | 0.03 | 0.02 | 0.02 |
| $\beta_{Contact,1990} - \bar{\beta}_{Contact}$ | -0.00 | -0.16 | -0.14 | -0.16 | 1.00 | -0.16 | -0.16 | -0.17 | 0.03 | 0.04 | 0.03 | -0.16 | 0.03 | 0.02 | 0.02 |
| $\beta_{Contact,2000} - \bar{\beta}_{Contact}$ | -0.00 | -0.15 | -0.15 | -0.16 | -0.16 | 1.01 | -0.17 | -0.17 | 0.04 | 0.04 | 0.04 | 0.03 | -0.15 | 0.02 | 0.02 |
| $\beta_{Contact,2012} - \bar{\beta}_{Contact}$ | 0.02 | -0.16 | -0.18 | -0.17 | -0.18 | -0.18 | 1.02 | -0.20 | 0.03 | 0.02 | 0.03 | 0.02 | 0.03 | -0.13 | 0.02 |
| $\beta_{Contact,2018} - \bar{\beta}_{Contact}$ | 0.03 | -0.16 | -0.18 | -0.17 | -0.18 | -0.18 | -0.19 | 1.04 | 0.03 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | -0.12 |
| $\beta_{Abstract,1960} - \bar{\beta}_{Abstract}$ | -0.14 | -0.08 | 0.01 | -0.00 | -0.00 | -0.01 | -0.01 | -0.01 | 1.32 | -0.23 | -0.25 | -0.25 | -0.25 | -0.25 | -0.25 |
| $\beta_{Abstract,1970} - \bar{\beta}_{Abstract}$ | -0.12 | 0.02 | -0.06 | 0.01 | 0.01 | 0.01 | 0.00 | 0.01 | -0.22 | 1.34 | -0.24 | -0.24 | -0.24 | -0.24 | -0.24 |
| $\beta_{Abstract,1980} - \bar{\beta}_{Abstract}$ | -0.09 | -0.00 | -0.01 | -0.06 | 0.00 | 0.00 | -0.00 | -0.00 | -0.24 | -0.25 | 1.36 | -0.24 | -0.24 | -0.23 | -0.23 |
| $\beta_{Abstract,1990} - \bar{\beta}_{Abstract}$ | -0.02 | 0.00 | -0.00 | 0.01 | -0.05 | 0.01 | 0.01 | 0.01 | -0.23 | -0.24 | -0.23 | 1.38 | -0.22 | -0.22 | -0.22 |
| $\beta_{Abstract,2000} - \bar{\beta}_{Abstract}$ | 0.05 | 0.01 | 0.00 | 0.01 | 0.01 | -0.04 | 0.01 | 0.01 | -0.22 | -0.23 | -0.22 | -0.22 | 1.38 | -0.21 | -0.22 |
| $\beta_{Abstract,2012} - \bar{\beta}_{Abstract}$ | 0.15 | 0.02 | 0.02 | 0.02 | 0.02 | 0.01 | -0.02 | 0.01 | -0.20 | -0.20 | -0.21 | -0.22 | -0.22 | 1.35 | -0.22 |
| $\beta_{Abstract,2018} - \bar{\beta}_{Abstract}$ | 0.18 | 0.03 | 0.03 | 0.02 | 0.02 | 0.02 | 0.01 | -0.02 | -0.20 | -0.20 | -0.21 | -0.21 | -0.21 | -0.21 | 1.39 |
| $\bar{\beta}_{Contact}$ | 0.33 | 0.49 | 1.00 | 0.50 | 0.59 | 0.52 | 0.58 | 0.62 | 0.53 | 0.64 | 0.39 | 0.29 | 0.12 | -0.02 | -0.04 |
| $\bar{\beta}_{Abstract}$ | 0.84 | 0.03 | 0.03 | 0.08 | 0.10 | 0.14 | 0.17 | 0.18 | 0.31 | 0.33 | 0.37 | 0.43 | 0.49 | 0.57 | 0.57 |
| $a_{Contact}$ | -0.03 | -0.19 | -0.45 | -0.20 | -0.24 | -0.20 | -0.23 | -0.25 | -0.26 | -0.32 | -0.18 | -0.12 | -0.03 | 0.05 | 0.06 |
| $a_{Abstract}$ | -0.28 | -0.01 | 0.02 | -0.03 | -0.04 | -0.06 | -0.06 | -0.06 | -0.08 | -0.09 | -0.12 | -0.16 | -0.20 | -0.25 | -0.25 |

*Notes:* Table presents the sensitivity of transformations of estimates of selected race-neutral parameters to Mincerian task premiums for *Contact* and *Abstract* tasks, in the case where we fix $\theta$ at the estimated value. the first column shows the parameter estimate; the remaining columns show the sensitivity. See the text for details.

Table R9: Sensitivity of $\theta$ to Aggregate Task Contents

| Panel A: | | Task Content, Contact | | | | | | | Task Content, Abstract | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Est. | 1960 | 1970 | 1980 | 1990 | 2000 | 2012 | 2018 | 1960 | 1970 | 1980 | 1990 | 2000 | 2012 | 2018 |
| $\theta$ | 3.60 | -0.46 | 0.36 | -0.04 | 0.17 | 0.15 | 0.26 | 0.34 | -2.97 | -2.96 | -2.33 | -1.14 | 0.26 | 2.24 | 2.73 |
| **Panel B:** | | **Task Premium, Contact** | | | | | | | **Task Premium, Abstract** | | | | | | |
| | Est. | 1960 | 1970 | 1980 | 1990 | 2000 | 2012 | 2018 | 1960 | 1970 | 1980 | 1990 | 2000 | 2012 | 2018 |
| $\theta$ | 3.60 | 7.20 | 4.83 | 2.86 | 0.56 | -1.84 | -4.97 | -5.82 | 9.30 | 8.35 | 6.87 | 2.78 | -1.72 | -7.67 | -9.38 |

*Notes:* Table presents the sensitivity of the estimated $\theta$ to aggregate task contents (Panel A) and Mincerian task premiums (Panel B) for *Contact* and *Abstract* tasks. The first column shows the parameter estimate; the remaining columns show the sensitivity. See the text for details.

### Appendix I.4.2 Sensitivity of Race-Specific Parameters

Lastly, we consider the sensitivity of race-specific parameters to moments on racial gaps. In the main text, we claimed that our estimation of race-specific parameters is equivalent to the following sequential procedure. First, we estimate the composite task-specific racial barriers $\delta_{kt}^b + \eta_{kt}^b + \gamma_{kt}^b$ and the racial gap in home sector returns $A_{Ht}^b$ jointly from the observed racial gaps in aggregate task contents and home sector shares. Next, we parse out the pecuniary and non-pecuniary components of task-specific barriers — i.e., $\delta_{kt}^b + \eta_{kt}^b$ versus $\gamma_{kt}^b$ — based on the observed racial gaps in Mincerian task premiums, noting that non-pecuniary discrimination $\gamma_{kt}^b$ does not impact labor market returns except through sorting. Last, we attribute any residual aggregate wage gap unexplained to the general non-task-related racial wedge $A_t^b$. We verify this assersion with the sensitivity analysis.

In particular, Table R10 presents the selected entries of the sensitivity matrix. To see the validity of our claim, note, for example, that racial gaps in task premiums have no impact on our estimates of $\delta_{kt}^b + \eta_{kt}^b + \gamma_{kt}^b$ and $A_{Ht}^b$; likewise, the aggregate racial wage gap has no impact on our estimates of $\gamma_{kt}^b$'s. This verifies the sequential nature of our estimation of race-specific parameters.

As it is intuitive, the table shows that a smaller (i.e., less negative) racial gap in aggregate task content for a task reduces the estimated composite racial barrier in the task (i.e., makes $\delta_{kt}^b + \eta_{kt}^b + \gamma_{kt}^b$ more positive for the task). Similarly, a smaller (i.e., less negative) racial gap in Mincerian task premium on a task reduces the estimated pecuniary racial barrier in the task (i.e., makes $\gamma_{kt}^b$ more negative). Finally, a smaller racial wage gap maps one-to-one to a less negative $A_t^b$, which is natural given that the parameter measures any residual racial wage gap unexplained by other race-specific parameters.

## Appendix I.5 Decomposition of the Evolution of Racial Wage Gap

In Sections 5.2, we quantify the contributions of the race-neutral and race-specific forces to the evolution of the racial wage gap over time. Specifically, we calculate the contribution of each of the model driving forces — $A_{Ht}$, $\beta_{kt}$'s, $\delta_{kt} + \eta_{kt}$'s, $\gamma_{kt}$'s, $A_t^b$, and $A_{Ht}^b$ — to the changing racial wage gap by linearly interpolating all the estimated variables over every two consecutive periods and integrating each term in the total derivative of the racial wage gap over time.

More formally, let $\vec{x}_t = (A_{Ht}\, \{\beta_{kt}\}_k,\, \{\delta_{kt} + \eta_{kt}\}_k,\, \{\gamma_{kt}\}_k,\, A_t^b, A_{Ht}^b)$ denote the vector of all model driving forces. To decompose the changes in the racial wage gap between 1980 and 1990, for example, we parameterize $\vec{x}$ over the period by $\vec{x}(s) = \vec{x}_{1980} + (\vec{x}_{1990} - \vec{x}_{1980})s$ for $s \in [0,1]$. Under this linear interpolation, the evolution of the racial wage gap $\overline{\omega}^{gap}(\vec{x}(s)) \equiv \overline{\omega}_b^{agg}(\vec{x}(s)) - \overline{\omega}_w^{agg}(\vec{x}(s))$ at each $s \in [0,1]$ will be governed by

$$
\begin{aligned}
\frac{d\overline{\omega}^{gap}(\vec{x}(s))}{ds} &= \frac{d\overline{\omega}^{gap}(\vec{x}(s))}{dA_H}\;[A_{H,1990} - A_{H,1980}] + \sum_k \frac{d\overline{\omega}^{gap}(\vec{x}(s))}{d\beta_k}\;[\beta_{k,1990} - \beta_{k,1980}] \\
&+ \sum_k \frac{d\overline{\omega}^{gap}(\vec{x}(s))}{d(\delta_k + \eta_k)}\;[(\delta_{bk,1990} + \eta_{bk,1990}) - (\delta_{k,1980} + \eta_{k,1980})] + \sum_k \frac{d\overline{\omega}^{gap}(\vec{x}(s))}{d\gamma_k}\;[\gamma_{k,1990} - \gamma_{bk,1980}] \\
&+ \frac{d\overline{\omega}^{gap}(\vec{x}(s))}{dA^b}\;\left[A^b_{1990} - A^b_{1980}\right] + \frac{d\overline{\omega}^{gap}(\vec{x}(s))}{dA^b_H}\;\left[A^b_{H,1990} - A^b_{H,1980}\right],
\end{aligned}
$$

where the derivatives are derived in Sections 2.7 and Appendix H.2 above.[A27] At each $s \in [0,1]$, the first line on the right-hand side captures the marginal contributions of race-neutral effects; the second line captures the marginal contributions of the task-specific racial barriers; and the last line captures the marginal contributions of the non-task-specific racial barriers. To calculate the *total* contribution of each model driving force to the racial wage gap over the entire 1980-1990 period, we integrate each term on the right-hand side over $s \in [0,1]$. For example, to quantify the contribution of the pecuniary racial barrier $\delta^b_{kt} + \eta^b_{kt}$ for task $k$ to the evolution of the racial wage gap over the 1980-1990 period, we evaluate

$$\int_0^1 \frac{d\overline{\omega}_b^{agg}(\vec{x}(s))}{d(\delta_{bk} + \eta_{bk})}\, ds\ \left[(\delta_{bk,1990} + \eta_{bk,1990}) - (\delta_{bk,1980} + \eta_{bk,1980})\right].$$

Since each term in the derivative is additive, the contribution of each of the model driving forces calculated this way will sum to the total change in the racial wage gap over the period.

[A27]In addition to these model driving forces, the task requirement in the home sector, $\tau_{Ht}$, varies slightly over time due to aggregation by year (see Appendix I.1). However, this is quantitatively inconsequential.

Table R10: Sensitivity of Selected Race-Specific Parameters to Race-Specific Moments

| | | Gaps in: | | | | | |
|---|---|---|---|---|---|---|---|
| 1960 | Est. | Home Share | TC, Cont. | TC, Abst. | TP, Cont. | TP, Abst. | Agg. Wage |
| $A_H^b$ | 0.16 | 0.28 | 0.19 | 0.00 | 0.00 | 0.00 | 0.00 |
| $\delta+\eta+\gamma$, Contact | -0.82 | 0.02 | 4.96 | -2.96 | 0.00 | 0.00 | 0.00 |
| $\delta+\eta+\gamma$, Abstract | -0.86 | -0.04 | 2.14 | 5.38 | 0.00 | 0.00 | 0.00 |
| $\gamma$, Contact | -0.89 | -0.08 | 9.54 | 2.89 | -9.99 | 0.00 | 0.00 |
| $\gamma$, Abstract | 0.02 | 0.17 | -0.93 | -0.24 | 0.00 | -4.82 | 0.00 |
| $A^b$ | -0.27 | -0.00 | 0.85 | 0.65 | -1.19 | -0.58 | 1.00 |
| 1970 | Est. | Home Share | TC, Cont. | TC, Abst. | TP, Cont. | TP, Abst. | Agg. Wage |
| $A_H^b$ | 0.14 | 0.28 | 0.04 | -0.12 | -0.00 | -0.00 | 0.00 |
| $\delta+\eta+\gamma$, Contact | -0.65 | 0.00 | 5.16 | -1.64 | 0.00 | 0.00 | 0.00 |
| $\delta+\eta+\gamma$, Abstract | -0.56 | -0.02 | 1.08 | 3.82 | 0.00 | 0.00 | 0.00 |
| $\gamma$, Contact | -0.91 | -0.04 | 7.90 | 1.90 | -8.30 | 0.00 | 0.00 |
| $\gamma$, Abstract | -0.02 | 0.12 | -0.60 | 0.21 | -0.00 | -4.68 | 0.00 |
| $A^b$ | -0.24 | 0.00 | 0.47 | 0.34 | -1.24 | -0.73 | 1.00 |
| 1980 | Est. | Home Share | TC, Cont. | TC, Abst. | TP, Cont. | TP, Abst. | Agg. Wage |
| $A_H^b$ | 0.16 | 0.27 | 0.09 | 0.01 | -0.00 | -0.00 | 0.00 |
| $\delta+\eta+\gamma$, Contact | -0.49 | 0.01 | 6.44 | -1.59 | 0.00 | 0.00 | 0.00 |
| $\delta+\eta+\gamma$, Abstract | -0.47 | -0.03 | 1.04 | 3.45 | 0.00 | 0.00 | 0.00 |
| $\gamma$, Contact | -0.67 | -0.06 | 9.70 | 2.30 | -9.73 | -0.00 | 0.00 |
| $\gamma$, Abstract | -0.09 | 0.11 | -0.55 | 0.30 | -0.00 | -4.48 | 0.00 |
| $A^b$ | -0.18 | -0.00 | 0.41 | 0.27 | -1.28 | -0.79 | 1.00 |
| 1990 | Est. | Home Share | TC, Cont. | TC, Abst. | TP, Cont. | TP, Abst. | Agg. Wage |
| $A_H^b$ | 0.18 | 0.28 | 0.12 | 0.02 | -0.00 | -0.00 | 0.00 |
| $\delta+\eta+\gamma$, Contact | -0.30 | 0.01 | 6.10 | -1.15 | 0.00 | 0.00 | 0.00 |
| $\delta+\eta+\gamma$, Abstract | -0.41 | -0.03 | 0.87 | 2.75 | 0.00 | 0.00 | 0.00 |
| $\gamma$, Contact | -0.33 | -0.06 | 9.03 | 1.99 | -9.00 | -0.00 | 0.00 |
| $\gamma$, Abstract | -0.06 | 0.11 | -0.45 | 0.26 | 0.00 | -4.11 | 0.00 |
| $A^b$ | -0.11 | -0.00 | 0.36 | 0.16 | -1.39 | -0.90 | 1.00 |
| 2000 | Est. | Home Share | TC, Cont. | TC, Abst. | TP, Cont. | TP, Abst. | Agg. Wage |
| $A_H^b$ | 0.21 | 0.30 | 0.09 | 0.01 | -0.00 | 0.00 | 0.00 |
| $\delta+\eta+\gamma$, Contact | -0.26 | 0.02 | 6.17 | -1.06 | 0.00 | 0.00 | 0.00 |
| $\delta+\eta+\gamma$, Abstract | -0.40 | -0.04 | 0.80 | 2.42 | 0.00 | 0.00 | 0.00 |
| $\gamma$, Contact | -0.12 | -0.12 | 9.13 | 1.99 | -8.92 | 0.00 | 0.00 |
| $\gamma$, Abstract | 0.00 | 0.17 | -0.44 | 0.17 | 0.00 | -3.78 | 0.00 |
| $A^b$ | -0.04 | -0.00 | 0.35 | 0.14 | -1.46 | -0.97 | 1.00 |
| 2012 | Est. | Home Share | TC, Cont. | TC, Abst. | TP, Cont. | TP, Abst. | Agg. Wage |
| $A_H^b$ | 0.14 | 0.31 | 0.16 | 0.07 | -0.00 | 0.00 | 0.00 |
| $\delta+\eta+\gamma$, Contact | -0.20 | 0.02 | 6.09 | -0.98 | 0.00 | 0.00 | 0.00 |
| $\delta+\eta+\gamma$, Abstract | -0.41 | -0.06 | 0.80 | 2.20 | 0.00 | 0.00 | 0.00 |
| $\gamma$, Contact | -0.16 | -0.15 | 8.82 | 1.96 | -8.39 | 0.00 | 0.00 |
| $\gamma$, Abstract | -0.02 | 0.19 | -0.41 | 0.08 | 0.00 | -3.40 | 0.00 |
| $A^b$ | -0.06 | -0.01 | 0.23 | 0.08 | -1.52 | -1.02 | 1.00 |
| 2018 | Est. | Home Share | TC, Cont. | TC, Abst. | TP, Cont. | TP, Abst. | Agg. Wage |
| $A_H^b$ | 0.11 | 0.28 | 0.11 | 0.07 | -0.00 | -0.00 | 0.00 |
| $\delta+\eta+\gamma$, Contact | -0.14 | 0.01 | 5.96 | -0.86 | 0.00 | 0.00 | 0.00 |
| $\delta+\eta+\gamma$, Abstract | -0.41 | -0.04 | 0.81 | 2.10 | -0.00 | 0.00 | 0.00 |
| $\gamma$, Contact | 0.02 | -0.09 | 8.50 | 1.87 | -8.05 | -0.00 | 0.00 |
| $\gamma$, Abstract | -0.05 | 0.11 | -0.31 | 0.12 | -0.00 | -3.28 | 0.00 |
| $A^b$ | -0.05 | -0.00 | 0.23 | 0.06 | -1.56 | -1.05 | 1.00 |

*Notes:* Table presents the sensitivity of estimates of selected race-specific parameters. the first column shows the parameter estimate; the remaining columns show the sensitivity. See the text for details.