Task-Based Discrimination

Erik Hurst

Yona Rubinstein

Kazuatsu Shimizu *

April 11, 2024

Abstract

In this paper, we develop a task-based model of occupational sorting to identify and quantify the effect of discrimination, racial skill gaps and aggregate task prices on Black-White differences in labor market outcomes over time. At the heart of our framework is the idea that the size and nature of racial barriers faced by Black workers varies by the task requirements of each job. We define a new task that measures the extent to which individuals interact with others as part of their job. Using both the structure of our model, detailed micro data from the Census/ACS and the NLSY, and regional variation in survey-based discrimination measures, we highlight that the racial gap in this new task measure is a good proxy for the extent of discrimination in the economy. Our structurally estimated model also provides insights into why Black men closed the racial gap in some occupations but not others during the 1960-2018 period. We also quantify the extent to which changing task prices contributed to the stagnation of the racial wage gap post-1980.

*Hurst: Department of Economics, University of Chicago (email: erik.hurst@chicagobooth.edu); Rubinstein: Department of Management, LSE, and Department of Economics, University of Houston (email: y.rubinstein@lse.ac.uk); Shimizu: Department of Economics, MIT (email: kazuatsu@mit.edu). We thank Jack Hurst for his help in constructing some of the data files used within the paper and Kevin Lang for providing us with a fantastic set of comments when he discussed our paper at the Fall 2021 NBER EFG meetings. We also thank Daron Acemoglu, David Autor, Pat Bayer, Joydeep Bhattacharya, Sandy Black, Kerwin Charles, David Deming, Chinhui Juhn, Patrick Kehoe, Pat Kline, David de Meza, Matt Notowidigdo, Elena Pastorino, and Pascual Restrepo for helpful comments as well as seminar participants at a variety of seminars.

1 Introduction

Despite various progress made since the passage of the Civil Rights Act in the 1960s, there remains a systematic difference in the occupations where Black and White men work. For example, in 1960, only 3 percent of employed Black men with a bachelor's degree worked in *Engineering* occupations; the comparable number for White men was 14 percent. This racial gap persists today with college-educated White men still being twice as likely to work in *Engineering* occupations as college-educated Black men.[1] However, in other occupations, more progress has been made. One such example is *Sales* occupations. Much like in *Engineering* occupations, only 2 percent of Black men with a bachelor's degree worked in *Sales* occupations in 1960; the comparable number for White men was 12 percent. Yet, by 2018, this racial gap disappeared with roughly 10 percent of each group working in *Sales* occupations.

Why is it that the racial gap closed in some occupations but remained persistently large in other occupations? Can the differential racial gaps across occupations help to shed light upon the potential barriers faced by Black men in the labor market? In this paper, we develop a framework that integrates notions of discrimination and racial differences in skills into a task-based model of occupational sorting to better understand the evolution of Black-White gaps in labor market outcomes within the United States during the last sixty years.[2] One of the main benefits of using task-based models is that they reduce the dimensionality of the occupational data by projecting over 300 detailed occupations onto a handful of common tasks that the occupations require. We highlight how racial differences in occupational sorting along task dimensions provides information about the nature of the barriers faced by Black men in the labor market and how those barriers have evolved over time.

At the heart of our framework is the idea that the size and nature of racial barriers faced by Black workers vary by the task requirements of each occupation. For example, one might imagine that labor market discrimination operates more in occupations that require interactions with others. To that end, one of the paper's first contributions is to define a new task measure – *Contact* – which is guided by Becker (1957)'s work on discrimination. Specifically, "*Contact*" tasks measure the extent to which an occupation requires interaction and communication with others within the organization (co-workers) or outside the organization (customers/clients). *Sales* occupations, discussed above, are among the occupations that have

[1] Author's calculations using data from the 1960 US Census and the pooled 2016-2018 American Community Surveys. Sample restrictions and the specific occupation measures are discussed in detail in Section 3. See Hurst et al. (2024) for the full replication package for all results discussed within the paper.

[2] There has been a large amount of recent work highlighting the importance of using a task-based approach to understand the evolution of inequality in the U.S. labor market during the last half-century. For example, see Autor et al. (2003), Dorn (2009), Autor and Dorn (2013), Acemoglu and Autor (2011), and Acemoglu and Restrepo (2021). We build on the above literature to learn about Black-White labor market inequality and, in doing so, better understand labor market barriers faced by Black men.

the highest *Contact* task requirements. We conjecture *ex-ante* — and verify *ex-post* through model estimation — that the racial gap in this task provides a measure of direct discrimination.[3] We then use detailed micro-data from various sources to provide additional supporting empirical evidence for this model-based finding.

The second main contribution of our task-based framework is to highlight that the existence of task-specific racial barriers implies that race-neutral changes in task prices can affect the evolution of the Black-White wage gap even when race-specific forces – such as direct labor market discrimination and racial skill gaps – remain fixed over time. The literature has shown that the labor market return to one task in particular – "*Abstract*" tasks – has grown sharply relative to the return to other tasks starting in the early 1980s. *Engineering* occupations in the above example are among the set of occupations with the highest *Abstract* task requirements. If Black men are systematically underrepresented in occupations requiring *Abstract* tasks or if they have on average a lower amount of skills required by *Abstract* tasks, then the rising labor market return to *Abstract* tasks will disadvantage Black workers relative to White workers, all else equal. We show both through the lens of our structural model and by using detailed micro-data from a variety of sources that the rising return to *Abstract* tasks post-1980 substantially widened the racial wage gap during the 1980-2018 period and masked the effect of narrowing racial skill gaps and declining direct discrimination that would have otherwise caused a sizeable convergence in the racial wage gap over the period. Our collective findings help explain why the racial wage gap has been essentially constant since 1980 despite the declining labor market discrimination and narrowing racial skill gaps over this period.

We begin our analysis by documenting a new set of facts about racial differences in occupational sorting along task dimensions.[4] In addition to the novel *Contact* tasks mentioned above, we take three commonly-used task measures from the existing literature: "*Abstract*", "*Routine*", and "*Manual*" tasks. These three task measures come directly from Dorn (2009) and Autor and Dorn (2013). Using micro-data from the US Censuses and American Community Surveys, we document that there was a large racial gap in the extent to which workers sort into occupations that require *Abstract* tasks in 1960 and that gap remained essentially constant through 2018. This finding holds regardless of whether we control for trends in racial gaps in accumulated levels of schooling. In contrast, the large racial gap in the extent to which workers sort into occupations requiring *Contact* tasks that existed in 1960 narrowed substantively by 2018. In sum, over the last sixty years, Black men have made little progress in sorting into occupations that primarily require *Abstract* tasks (like *Engineering*) but substantial progress

[3] Throughout, we define *direct discrimination* as the differential treatment of Black men in the labor market conditional on observed skills. For a similar definition, see recent work by Bohren et al. (2022).

[4] There is an existing literature documenting racial differences across broad occupational categories. For example, see Altonji and Blank (1999) or Chetty et al. (2020). Our innovation is to document racial gaps in occupational sorting along task dimensions and then show how those gaps have evolved over time.

in sorting into occupations that primarily require *Contact* tasks (like *Sales*).

Our next key contribution is to develop a framework of occupational choice that separates various race-specific demand and supply forces and guides our empirical work in the rest of the paper. In our model, individuals are endowed with task-specific skills that are drawn from a known distribution. There are many potential tasks and, in turn, many different types of skills. Occupations are combinations of tasks with different weights and individuals have different mixtures of skills. Absent racial barriers, individuals sort into occupations that maximize their utility, which is a combination of the wage and their idiosyncratic job preferences. In this basic setting, we introduce racial barriers that are specific to each type of task. The existence of these task-specific racial barriers gives rise to differential occupational sorting along task dimensions between Black and White individuals in the spirit of Roy (1951).

Specifically, we consider three types of task-specific racial barriers in the model. First, we allow Black and White men to have, on average, different levels of task-specific skills. The racial gaps in task-specific skills reflect current and past discrimination that impacts the skill formation and skill development of Black workers.[5] Second, we allow for *pecuniary* task-specific discrimination. This force reflects either Beckerian motives so that Black men may be paid less for certain tasks they perform relative to their White counterparts with the same level of skills or statistical discrimination if employers do not observe worker skills perfectly. Finally, we allow for *non-pecuniary* task-specific discrimination. This force captures the possibility that Black workers may get explicitly rationed from occupations requiring certain tasks or face higher disutility from discrimination in occupations requiring certain tasks. We allow for all three of these forces to differ across tasks and to evolve differentially over time.

We estimate the key race-specific and race-neutral driving forces in our model using detailed micro-data from the U.S. Censuses and American Community Surveys. We first estimate race-neutral forces such as task prices from the labor market returns and occupational choices of White men. Our estimates confirm that the return to *Abstract* tasks increased sharply post-1980 relative to other task prices. With these estimates of race-neutral parameters in hand, we infer the *composite* racial barrier for each task — the sum of all three task-specific racial barriers (racial skill gaps, pecuniary discrimination, and non-pecuniary discrimination) — from the extent of differential sorting between Black and White men along each task dimension. We find that the composite racial barrier for both *Abstract* and *Routine* tasks fell sharply between 1960 and 1990 and then remained constant thereafter. Conversely, the racial barrier for *Contact* tasks fell continuously between 1960 and 2018.

[5] We wish to stress that our model does not imply that there are potentially innate skill differences between Black and White workers. Instead, to the extent that racial gaps in labor market skills exist, they are almost certainly the artifact of past discrimination which affects skill formation in early ages (Heckman et al. (2006)) or the influence of differential access to schooling and job training later in life (Coate and Loury (1993)).

We then proceed to parse out the composite racial task barriers into non-pecuniary and pecuniary components. The two pecuniary task-specific racial barriers – racial skill gaps and pecuniary discrimination – directly affect task returns while non-pecuniary task-specific discrimination does so only indirectly through its impact on occupational sorting. As a result, we can infer the size of pecuniary racial barriers for each task from the observed racial gaps in task returns. Here, we leverage the model structure to correct for selection which tends to mask racial gaps in task returns. Based on this procedure, we estimate that essentially all of the composite racial barrier for *Contact* tasks – in both levels and changes – was due to non-pecuniary discrimination. This means that Black men were either explicitly excluded from occupations requiring *Contact* tasks or Black men experienced additional disutility from working in occupations requiring *Contact* tasks due to discrimination from co-workers and customers; however, conditional on working in such occupations, Black men were paid the same task returns, on average, as White men with comparable skills.

Importantly, the finding that the racial barrier in *Contact* tasks is almost all non-pecuniary verifies our conjecture that the racial gap in *Contact* tasks is a good proxy for direct discrimination in the labor market. Racial skill gaps are inherently pecuniary, so our model suggests they cannot be a meaningful component of the racial barrier in *Contact* tasks. As a point of contrast, we estimate that a substantial component of the composite racial barrier in *Abstract* tasks is due to a combination of racial skill gaps and pecuniary discrimination; Black men working in *Abstract* tasks earn, on average, lower task returns compared to White men conditional on selection. Combining our structural model with additional micro-data from the National Longitudingal Survey of Youths (NLSY), we decompose the composite racial barrier in *Abstract* tasks into a racial skill difference and direct discrimination. This procedure finds that about half of the racial barrier in *Abstract* tasks is, in fact, due to the racial gap in skills associated with *Abstract* tasks.

We use micro-data from many additional sources and exploit regional variation to provide further empirical support for our finding that the racial gap in *Contact* tasks is a good proxy for direct discrimination. For example, in one of our exercises, we use data from Charles and Guryan (2008) which provides survey-based measures of direct discrimination for each U.S. state based on questions from the General Social Survey. Using cross-state variation, we show that racial gaps in *Contact* tasks are strongly correlated with the Charles-Guryan state-level survey measures of direct discrimination as predicted by our model. In contrast, we find no correlation between state-level measures of racial gaps in *Abstract* tasks and the Charles-Guryan survey measures of state-level discrimination. Collectively, these additional results provide further empirical support for our model prediction that the racial gap in *Contact* tasks is a good proxy for direct racial discrimination while the racial gap in *Abstract* tasks is largely driven by pecuniary barriers such as racial skill gaps.[6]

The second of our two main contributions is to assess how changing task returns help explain the stagnation of the racial wage gap post-1980. In 1960, the log wages of Black men were about 40 log points lower than White men conditional on education. That gap shrunk to about 20 log points by 1980, but then the convergence stagnated and the gap remained roughly constant through 2018. Concurrently, we saw the return to *Abstract* tasks rise continually post-1980. Our task-based framework of discrimination links these developments to shed light on the mechanisms underlying the stagnation of the racial wage gap post-1980.

Specifically, the model implies that, given the high racial barriers Black men face in *Abstract* tasks, an increase in the *Abstract* task price will widen the racial wage gap through two channels. First, the systemic under-representation of Black workers in occupations requiring *Abstract* tasks implies that fewer Black workers benefit from the increase in wages in these occupations. Second, even for Black workers who have sorted into occupations requiring *Abstract* tasks, if they have lower *Abstract* skills on average, or if pecuniary discrimination makes them paid as if they had lower *Abstract* skills, then on average they benefit less from the rising *Abstract* task price than White workers in the same occupation.

Our estimated model suggests that the stagnation in the racial wage gap post-1980 is a product of two roughly offsetting forces. On the one hand, a narrowing of the race-specific forces between 1980 and 2018 caused the racial wage gap to close by about 5.5 log points – a roughly 25% decline – during this period. On the other hand, the changing returns to tasks since 1980 – particularly the increasing return to *Abstract* tasks – widened the racial wage gap by about 7.0 log points during the same period. This is because of the two channels outlined above. As a point of comparison, we show that the relative wage gains of Black men during the earlier 1960-1980 period stemmed solely from improving race-specific factors consistent with the literature highlighting the importance of the Civil Rights Act or change in the minimum wage in reducing racial wage gaps during this period.[7] Given that the labor market returns to the various task measures trended similarly between 1960 and 1980, changing task prices did not mask any of the race-specific gains during this earlier period.

[6]Contemporaneously, Kline et al. (2021) use a large-scale randomized experiment sending out fictitious job applications to large employers. They find that some firms are still unwilling to interview applications with Black sounding names. Consistent with our findings, they document that the racial gap in call-back rates was highest in occupations that require workers to interact with customers. This finding provides additional supportive evidence that the racial gap in *Contact* tasks is a good proxy for direct labor market discrimination.

[7]We find that a large part of our estimated race-specific gains during the entire sample period stems from an improvement in non-task-specific forces. The non-task-related forces embedded in our model capture changes in the racial wage gap due to aggregate policies like Civil Rights legislation that reduces discrimination in all tasks (e.g., Freeman (1973), Donohue and Heckman (1991)), changes in minimum wage policy (e.g., Derenoncourt and Montialoux (2020)), relative improvements in Blacks' overall school quality which effects general (non-task specific) education (e.g., Smith and Welch (1989), Card and Krueger (1992)) or changes in the returns to general (non-task-specific) education (e.g., Bayer and Charles (2018)).

We estimate that the narrowing of the racial wage gap coming from the convergence in task-specific skills or declining pecuniary discrimination slowed down for the country as a whole in the 2000s. We also estimate our model separately for different U.S. regions. Our regional analysis suggests that direct labor market discrimination had become small in the Non-South regions by 1990 and hence there was less room for further improvements. In contrast, in the South region, where direct discrimination was more perverse, the decline in racial barriers continued through 2018. Our model thus provides an explanation for why racial wage gaps *widened* in the Non-South regions post-1980 while they continued to *narrow* in the South region post-1980. In the Non-South regions, where survey based measures of discrimination are relatively smaller, the primary effect on the racial wage gap was the increasing return to *Abstract* tasks which favored White workers. In the South regions, the declining discrimination and the narrowing of the racial skill gaps that occurred during the 1980s, 1990s, and 2000s more than offset the effect of rising *Abstract* task returns.

Our structural model provides a road map to empiricists looking to uncover changing race-specific factors in micro-data. Specifically, the model suggests that researchers must control for *changes* in the returns to different tasks when analyzing racial wage gaps over time if they wish to isolate the effects of changing race-specific factors. We perform two model-guided empirical exercises to assess the model predictions by explicitly controlling for changing task returns in wage regressions. Both of these reduced form regressions show that (i) changing task returns caused the racial wage gap to widen by roughly the same magnitude as predicted by the model and (ii) controlling for time-varying changes in task returns uncovers a narrowing of the racial wage gap consistent with the predictions of the model. Collectively, these results provide direct support for our model's structural findings that changing task returns post-1980 caused the aggregate racial wage gap to widen and that changing *Abstract* task prices masked the labor market progress Black men made from narrowing racial skill gaps and declining discrimination.

Our paper builds on important insights from Juhn et al. (1991) and Bayer and Charles (2018) who non-parametrically estimate how changes in aggregate returns to skills and the decline in racial barriers have affected the Black-White earnings gap. Juhn et al. (1991) decomposes trends in racial earning gaps into the effects of race-neutral and race-specific forces under the assumption that worker skills are represented by a single aggregate index. The seminal work by Bayer and Charles (2018) extends the methodology by allowing for two dimensions of individual skills: educational attainment and residual skills. We expand on the insights of Bayer and Charles (2018) in three ways. First, Bayer and Charles (2018) document that the increasing return to education disadvantaged Black men during the last few decades given that Black men, on average, had lower levels of education than their White counterparts. We make a similar argument but with respect to changing task returns conditional on education. Through empirical exercises suggested by the model, we document that changing task returns conditional on education were just as important quantitatively in causing the racial wage gap to widen post-1980 as changing education returns. Second, by including a vector of worker skills for different types of occupations, our task-based framework allows us to jointly explain the evolution of both racial differences in occupational sorting and the racial wage gap since 1960. Finally, and most importantly, we show that by looking at the evolution of racial differences in occupational sorting along task dimensions, one can better distinguish among the potential underlying barriers faced by Black men during this time period. For example, we highlight that the racial gap in *Contact* tasks provides a good proxy for direct labor market discrimination faced by Black men and document a significant decline in the *Contact* task gap over the past half-century.[8]

The rest of the paper is organized as follows. Section 2 develops our model of task-based sorting with racial barriers. Section 3 uses micro-data from the Census and American Community Surveys to document how racial differences in occupational sorting along various task dimensions have evolved over time. Section 4 explains how we estimate the model and infer racial barriers from the racial differences in occupational sorting. Section 5 presents estimates of model parameters and the key results from our estimated model. In Section 6, we implement our model-guided empirical specifications to isolate the effects of changing task returns and changing race-specific driving forces on the evolution of the racial wage gap over time. Section 7 uses regional variation to provide supporting evidence for our key model result that the racial gap in *Contact* tasks is primarily driven by direct labor market discrimination. We bring in additional data from the NLSY in Section 8 to assess the importance of racial skill gaps in explaining the racial gap in *Abstract* tasks. The final section concludes.

2 A Theory of Task Based Discrimination and Occupational Sorting

To guide our empirical work in the rest of the paper, we develop a task-based framework of occupational choice that allows for task-specific racial barriers. There are over 300 detailed occupation codes in Census data; the benefit of the task approach is that in reduces the dimensionality of the occupation data to a handful of common task components. Our model builds upon Autor and Handel (2013), which proposes a Roy model where workers with

[8]Our paper is also related to Hsieh et al. (2019) which proposes and estimates a multi-sector Roy model of occupational sorting with workers of different races and genders to assess the role of changing racial and gender barriers during the last half century contributed to economic growth.

differential skill endowments self-select into occupations according to their task requirements. We extend their framework by introducing *race-specific* barriers, namely racial differences in underlying task-specific skills and the existence of labor market discrimination. These race-specific barriers will create differential sorting patterns between Black and White workers across occupations with different task intensities. Furthermore, the existence of race-specific barriers implies that *race-neutral* driving forces – such as changing task returns over time – can impact wages and occupational choices of Black and White men differentially. Finally, the framework suggests a reduced-form empirical methodology for uncovering changes in race-specific driving forces using micro data on wages and occupational choices.

2.1 Occupations

Occupations are characterized by their task requirements. Specifically, occupations are represented as bundles of K tasks, where the relative importance of tasks differs across occupations. We denote the task content of occupation o with a vector $T_o = (\tau_{o1}, ..., \tau_{oK}) \in \mathcal{R}_+^K$. An occupation may require a relatively high amount of one task, relatively high amounts of multiple (or even all) tasks, or relatively low amounts of all tasks.

2.2 Worker Heterogeneity

Workers belong to different groups g. In our application, g denotes White men ($g{=}w$) or Black men ($g{=}b$). Groups differ from each other in three task-specific ways. First, groups may differ in their task-specific "skill" endowments. This can proxy for the effects of current and past discrimination which affect the level of a worker's task-specific human capital. Second, a given group may face something akin to direct discrimination in a particular task in the spirit of Becker (1957); conditional on their task-specific skills, workers of a given group may be paid less than their marginal product. This may potentially include statistical discrimination if employers do not observe worker skills perfectly. Third, in addition to the *pecuniary* discrimination that creates a wedge in task returns of otherwise identical workers, we also allow for task-specific *non-pecuniary* discrimination that impacts occupational choices of Black workers relative to White workers over and beyond racial differences in pecuniary returns. This force proxies for the possibility that workers may either be rationed from occupations that require certain tasks or be treated poorly if they work in occupations requiring such tasks.[9]

[9] While we do not formally model the micro foundation of these wedges, the literature has suggested a few explanations for why Beckerian discrimination might not be competed away. For example, it could be that a sufficiently high fraction of employers are discriminatory (as in Becker (1957)) or that workers face search friction in matching with the potential employers (as in Black (1995)), so that Black workers cannot fully sort away from discriminatory employers within each sector. The pecuniary wedges in our model are proxies for these forces. See Hsieh et al. (2019) for a similar approach.

We also allow for two racial differences that are not task-specific. In particular, we allow for a general (i.e., non-task-related) racial barrier that impacts the racial wage gap above and beyond the task-specific barriers discussed above. Finally, we allow groups to differ in their reservation utility in the home sector. This last feature accounts for differential employment rates across groups conditional on other model driving forces.[10] All five of these group-specific differences are allowed to evolve differentially over time. We now specify the details of worker heterogeneity within and across groups.

Task-Specific Skills All workers perform tasks by allocating a unit of labor to the occupation of their choice, but workers differ in their efficiencies at performing each type of tasks, which are drawn from a known distribution. Omitting time subscripts, we denote the skill-endowment of worker i belonging to group g with a vector $\overrightarrow{\phi_{ik}^{g}} = \{\phi_{i1}^{g}, ..., \phi_{iK}^{g}\} \in \mathcal{R}_{+}^{K}$, where ϕ_{ik}^{g} denotes the efficiency units of worker i from group g in task k. If there are K tasks, individuals will receive K skill draws. The skill draws are constant over a worker's life.

We allow the mean of the skill distributions to differ across racial groups. For White men (g=w), we assume that the skill draws are given by $\overrightarrow{\phi_{ik}^{w}} = \{\phi_{i1}, ..., \phi_{iK}\}$, where each ϕ_{ik} is drawn from a Frechet distribution with shape parameter θ_k and scale parameter 1, both of which are constant over time. For Black men (g=b), we assume the vector of skill draws can be expressed as $\overrightarrow{\phi_{ik}^{b}} = \{\eta_1^b + \phi_{i1}, ..., \eta_K^b + \phi_{iK}\}$, where η_k^b measures the gap in average task-specific skills between Black and White men. In short, the skill distribution for Black men in each task k is shifted by η_k^b relative to that for White men. The existence of task-specific racial skill gaps does not imply that there are innate skill differences across racial groups; instead the η_k^b's proxy for the fact that current and past discrimination can result in different groups having different levels of task-specific human capital at a given point in time.

We allow the η_k^b's to differ by task and to evolve differentially over time; hence, changes in task-specific racial skill gaps will in part drive the evolution of the racial wage gap and racial gaps in occupational sorting. Thus, we hereafter include the time subscript and write η_{kt}^b.

Occupational Preferences Workers also draw occupational preferences from a known distribution. We denote the occupational preferences of worker i belonging to group g with a vector $\overrightarrow{\nu_{io}} = \{\nu_{i1}, ..., \nu_{iO}\} \in \mathcal{R}_{+}^{O}$. We assume that each ν_{io} is drawn from a Frechet distribution with shape parameter ψ and scale parameter 1, both of which are common across groups and constant over time. These idiosyncratic occupational preferences are a reduced form for any sorting frictions that may be present in reality; they help the model to match the distribution

[10] Chandra (2000), Heckman et al. (2000) and Bayer and Charles (2018) caution the literature about focusing on mean racial wage gaps over time given differential trends in labor force participation between Black and White men. For this reason, we explicitly include a margin of labor force participation in the model.

of occupational sorting observed in the data.

Collectively, individual i is defined by $\overrightarrow{\phi_{ik}^{g}}$ (the vector of K task-specific skill draws), $\overrightarrow{\nu_{io}}$ (the vector of O occupation-specific preference draws), and g (the group affiliation).

2.3 Worker Wages

In the presence of racial skill gaps and direct discrimination, the labor market wages of Black and White workers may differ systematically. Define the potential log wage ω_{iot}^{w} that worker i belonging to race group White men (g=w) would earn in occupation o in period t as:

$$\omega_{iot}^{w} = A_t + A_o + \sum_{K} \beta_{kt}\tau_{ok}\phi_{ik}, \tag{1}$$

where A_t is an aggregate time-effect common to all workers capturing forces such as general technological progress; A_o is an occupation-specific constant representing the log wage that a worker with no skills would earn in occupation o beyond A_t; and $\beta_{kt} \geq 0$ is the price of each task, which is allowed to vary over time. By varying β_{kt} over time, we explore how changing returns to different tasks influence occupational sorting and the racial wage gap.[11]

Analogously, define the potential log wage ω_{iot}^{b} that worker i belonging to race group Black men (g=b) would earn in occupation o in period t as:

$$\omega_{iot}^{b} = A_t + A_t^{b} + A_o + \sum_{K} \beta_{kt}\tau_{ok}\left((\delta_{kt}^{b} + \eta_{kt}^{b}) + \phi_{ik}\right), \tag{2}$$

where A_t, A_o, β_{kt}, and τ_{ok} are as defined above. Then, conditional on their draws of ϕ_{ik}'s, Black workers may earn different wages than White workers in a given occupation for three reasons. First, there could be differences in average task-specific skills between the groups (the η_{kt}^{b}'s), as defined above. Second, there could be task-specific direct *pecuniary* discrimination affecting Black workers (the δ_{kt}^{b}'s). This proxies for anything that creates racial differences in task returns conditional on skills, including statistical discrimination which may arise when employers do not perfectly observe worker skills.[12] The composite pecuniary barrier $\delta_{kt}^{b} + \eta_{kt}^{b}$ causes the marginal return to tasks to differ systematically between Black and White workers.

[11]Note, in our baseline model, we assume the task content of occupations τ_{ok} to be time-invariant; we explore the sensitivity of our results to this assumption in our empirical work.

[12]In Appendix G, we extend the model to include noisily observed skills on the part of the employers. This extension led to a richer discussion of statistical discrimination when we allow for differences in mean skill levels between groups. However, for all of our key findings in this paper, explicit modeling of statistical discrimination was not necessary; one could think of statistical discrimination as constituting a part of the pecuniary discrimination term δ_{kt}^{b}. For parsimony, we removed our discussion of statistical discrimination from the main text and refer readers to the appendix for the full model with statistical discrimination and a discussion of how allowing for statistical discrimination does not change the paper's key results.

Finally, we allow for a general (i.e., non-task-specific) aggregate racial barrier, A_t^b, which creates a wedge in the wages earned by Black and White workers above and beyond the η_{kt}^b's and δ_{kt}^b's. This term captures any non-task-related barriers faced by Black men that systematically affect their wages relative to White men, such as (i) any aggregate racial skill (education) gap that is orthogonal to any of our four task measures, (ii) aggregate discrimination not directly linked to any of our four task measures, or (iii) any aggregate policy change that differentially affects Black workers regardless of their task content. For example, the A_t^b's might proxy for changes in the minimum wage that disproportionally help black workers (Derenoncourt and Montialoux (2020)), changes in aggregate discrimination stemming from forces such as the Civil Rights movement that are unrelated to the specific task contents of an occupation (Donohue and Heckman (1991)), changes in trends in unionization which could differentially affect Black worker wages regardless of occupational task content (Rosenfeld and Kleykamp (2012)), or changes in the returns to general education unrelated to the task content of an occupation that differentially affect Black workers relative to White workers (Bayer and Charles (2018)). Since the A_t^b's shift Black workers' wages in all occupations by the same amount in a given year, they do not affect occupational sorting. As a result, the A_t^b's will explain any residual racial wage gap after controlling for the task-specific barriers $(\eta_{kt}^b + \delta_{kt}^b)$'s.

2.4 Worker Utility

The final source for racial differences in occupational sorting is what we call non-pecuniary task-based discrimination. This force may reflect employers rationing Black workers out of occupations along certain task dimensions. Alternatively, it may reflect disutility from discrimination Black workers experience in occupations requiring certain tasks. However, conditional on employment, this force does not impact the wage Black men receive relative to White men.

Formally, the utility u_{iot}^g that worker i of group g attains in occupation o is the sum of the log earnings ω_{iot}^g, disutility due to non-pecuniary task-specific discrimination γ_{kt}^g, and idiosyncratic preference for occupations $\log \nu_{io}$:[13]

$$\begin{aligned} u_{iot}^g &\equiv \omega_{iot}^g + \sum_k \beta_{kt}\tau_{ok}\gamma_{kt}^g + \log \nu_{io} \\ &= A_t + A_t^g + A_o + \sum_k \beta_{kt}\tau_{ok}\left((\delta_{kt}^g + \eta_{kt}^g + \gamma_{kt}^g) + \phi_{ik}\right) + \log \nu_{io}, \end{aligned} \tag{3}$$

where we normalize $\gamma_{kt}^w = \delta_{kt}^w = \eta_{kt}^w = A_t^w = 0$ for White men for all tasks k in all periods t. Thus, non-pecuniary task-based discrimination γ_{kt}^b impacts worker utility (and hence their occupational choice) over and beyond pecuniary wedges in task returns arising from racial

[13]The γ's are multiplied by the β's and τ's so that the utility terms are in similar units as skills ϕ_{ik}.

skill gaps and pecuniary discrimination $(\delta^g_{kt} + \eta^g_{kt})$.

2.5 Home Sector

We complete the model by allowing for a "home sector", denoted as $o{=}H$. Adding a home sector allows us to model an extensive margin of labor supply. We treat the home sector as another potential occupation with task requirements $\tau_{H1}, ..., \tau_{HK}$ and (non-pecuniary) occupational return A^g_{Ht}.

The workers compare their utility from working (shown in equation (3)) to their reservation utility from being in the home sector:

$$u^g_{iHt} \equiv A_t + A^g_t + A^g_{Ht} + \sum_k \beta_{kt}\tau_{Hk}\left(\delta^g_{kt} + \eta^g_{kt} + \gamma^g_{kt} + \phi_{ik}\right) + \log \nu_{iH}. \tag{4}$$

We allow the reservation utility in the home sector, A^g_{Ht}, to differ by group g. For White men, we define $A^g_{Ht} = A_{Ht}$ while for Black men, we set $A^g_{Ht} = A_{Ht} + A^b_{Ht}$. A^b_{Ht} thus capture any additional forces aside from the η^b_{kt}'s, δ^b_{kt}'s, γ^b_{kt}'s and A^b_t's that may create labor supply differences between racial groups. A^b_{Ht} captures any discrimination Black workers face in the home sector as well as any general (i.e., non-task-related) non-pecuniary discrimination they may experience when working in any occupation.

2.6 Occupational Choice

Given an individual's task productivity draws $(\overrightarrow{\phi^g_{ik}})$, their occupational preference draws $(\overrightarrow{\nu_{io}})$, the task composition of occupations (τ_{ok}), the occupation and task prices they face (A_t's, A_o's, A^b_t's and β_{kt}'s), and any other task-specific racial barriers $(\delta^b_{kt}+\gamma^b_{kt})$, workers sort into different occupations so as to maximize their utility. The optimal occupational choice of worker i in group g in year t is given by

$$o^{*g}_{it} = \arg\max_{o=1,...,O,H}\left\{u^g_{iot}\right\}. \tag{5}$$

Everything else equal, occupations that require a large amount of one type of task tend to attract workers who are good at performing that type of task. So an occupation that requires more of task k (e.g., has a high τ_{ok}) will tend to attract workers with higher skills associated with that task (e.g., workers with higher ϕ_{ik}'s).

Recall that idiosyncratic occupational preferences ν_{io} follow a Frechet distribution with shape parameter ψ. This implies convenient closed-form expressions for occupational shares. As derived in Appendix H, 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:

Table 1: Summary of Race-Specific Barriers

	Task-Specific	General (Non-Task-Related)
Pecuniary	δ^b_{kt}'s, η^b_{kt}'s	A^b_t's
Non-Pecuniary	γ^b_{kt}'s	A^b_{Ht}'s

Notes: Table summarizes the five race-specific barriers that are included in the model.

$$\rho^g_{ot}(\vec{\phi}) = \frac{\exp\{\psi \hat{u}^g_{ot}(\vec{\phi})\}}{\sum_{o' \neq H} \exp\{\psi \hat{u}^g_{o't}(\vec{\phi})\}}, \tag{6}$$

where $\hat{u}^g_{ot}(\vec{\phi}) = A_t + A^g_t + A_o + \sum_k \beta_{kt}\tau_{ok}\left((\delta^g_{kt} + \eta^g_{kt} + \gamma^g_{kt}) + \phi_{ik}\right)$ is the non-idiosyncratic component of the utility that a worker of group g with skill draws $\vec{\phi}$ would attain in occupation o. An analogous expression gives the share of the home sector.

Table 1 summarizes the race-specific barriers in the model. The barriers facing Black workers can be either task-specific or general, and furthermore they can be pecuniary or non-pecuniary. Only the task-specific barriers (η^b_{kt}'s, δ^b_{kt}'s, and γ^b_{kt}'s) determine racial differences in occupational choice conditional on working. In particular, the A^b_t's will not affect occupational sorting, as it impacts wages of Black workers in all occupations equally. Likewise, only pecuniary barriers (η^b_{kt}'s, δ^b_{kt}'s, and A^b_t's) directly affect racial differences in labor market returns; non-pecuniary forces affect them only indirectly through their impact on occupational sorting. The task-specific racial barriers – racial skill gaps η^b_{kt}, pecuniary task-based discrimination δ^b_{kt}, and non-pecuniary task-based discrimination γ^b_{kt} – will play the central role in our analysis. The general pecuniary racial barriers (A^b_t's) and the racial differences in (non-pecuniary) home sector return (A^b_{Ht}'s) will capture all forces that are outside the task-specific portion of the model but contribute to the racial wage gap and the racial difference in employment rates.

2.7 Comparative Statics and Model Implications

The model includes *race-neutral* driving forces that may differentially affect the labor market outcomes of Black and White men over time, as well as *race-specific* barriers that cause the occupational choice and wages of Black and White men to diverge from each other. We next derive some key comparative static results of the model with respect to changes in both the race-neutral (the β_{kt}'s) and race-specific driving forces (the η^b_{kt}'s, δ^b_{kt}'s, γ^b_{kt}'s, and A^b_t's).[14]

[14] Appendix H contains the full details of the derivations as well as containing additional model results.

First, we consider comparative statics on the overall composition of tasks performed by Black and White workers. To that end, define the *average task content* performed by group g workers with skill draws $\vec{\phi}$ by $\overline{\tau}^g_{kt}(\vec{\phi}) = \sum_o \rho^g_{ot}(\vec{\phi})\tau_{ok}$. Proposition 1 examines how occupational sorting measured by the average task contents $\overline{\tau}^g_{kt}(\vec{\phi})$ changes in response to both changes in task prices (β_{kt}) and the composite task-specific racial barriers ($\eta^g_{kt} + \delta^g_{kt} + \gamma^g_{kt}$).

Proposition 1. *Race-neutral and race-specific forces impact the average task content $\overline{\tau}^g_{kt}(\vec{\phi})$ performed by group g workers with skill draws $\vec{\phi}$ according to:*

$$\frac{d\overline{\tau}^g_{kt}(\vec{\phi})}{d\beta_{kt}} = \psi \text{var}_{g,\vec{\phi}}(\tau_{ok})(\phi_k + \eta^g_{kt} + \delta^g_{kt} + \gamma^g_{kt}),$$

$$\frac{d\overline{\tau}^g_{kt}(\vec{\phi})}{d(\eta^g_{kt} + \delta^g_{kt} + \gamma^g_{kt})} = \psi \text{var}_{g,\vec{\phi}}(\tau_{ok})\beta_k \geq 0,$$

where $\text{var}_{g,\vec{\phi}}(\tau_{ok}) = \sum_o \rho^g_{ot}(\vec{\phi})(\tau_{ok} - \overline{\tau}^g_{kt}(\vec{\phi}))^2$ *denotes the variance of tasks performed τ_{ok} among group g workers with skill draws $\vec{\phi}$.*

The first equation shows that a rise in the return to task k tends to induce workers skilled in the task to move towards occupations with a higher requirement of that task; however, the composite race-specific task barriers ($\eta^b_{kt} + \delta^b_{kt} + \gamma^b_{kt}$) can hinder the extent of the movement for Black workers. In other words, the presence of task-specific barriers lowers the responsiveness of changing occupational sorting for Black men when aggregate task prices change. The second equation shows that the increase in the race-specific task barriers for a task (i.e., a more negative ($\eta^b_{kt} + \delta^b_{kt} + \gamma^b_{kt}$)) deters Black workers from sorting into occupations with high requirement for the task. Importantly, Proposition 1 implies that differences in the aggregate task content of occupations between Black and White men are key statistics that can help us infer the size of the combined race-specific task barriers ($\eta^b_{kt} + \delta^b_{kt} + \gamma^b_{kt}$) from the data given estimates for task returns β_{kt} and other distributional assumptions.

Proposition 2 derive comparative statics on the mean (log) wage received by group g workers with skill draws $\vec{\phi}$, denoted with $\overline{\omega}^g_t(\vec{\phi})$, with respect to key model driving forces.

Proposition 2. *Race-neutral and race-specific forces impact the mean (log) wage $\overline{\omega}^g_t(\vec{\phi}) = \sum_{o \neq H} \rho^g_{ot}(\vec{\phi})\omega^g_{ot}(\vec{\phi})$ earned by group g workers with skill draws $\vec{\phi}$ as follows:*

$$\frac{d\overline{\omega}^g_t(\vec{\phi})}{d\beta_{kt}} = \left[\overline{\tau}^g_{kt}(\bar{\phi}) + \psi \, \text{cov}_{g,\bar{\phi}}(\omega^g_{ot}(\vec{\phi}), \tau_{ok})\right](\phi_k + \eta^g_{kt} + \delta^g_{kt}),$$

$$\frac{d\overline{\omega}^g_t(\vec{\phi})}{d(\eta^g_{kt} + \delta^g_{kt})} = \left[\overline{\tau}^g_{kt}(\bar{\phi}) + \psi \, \text{cov}_{g,\bar{\phi}}(\omega^g_{ot}(\vec{\phi}), \tau_{ok})\right]\beta_{kt},$$

$$\frac{d\overline{\omega}_t^g(\vec{\phi})}{d\gamma_{kt}^g} = \left[0 + \psi \operatorname{cov}_{g,\bar{\phi}}(\omega_{ot}^g(\vec{\phi}), \tau_{ok})\right] \beta_{kt},$$

where $\operatorname{cov}_{g,\bar{\phi}}(\omega_{ot}^g(\vec{\phi}), \tau_{ok}) = \sum_{o \neq H} \rho_{ot}^g(\bar{\phi})(\omega_{ot}^g(\vec{\phi}) - \overline{\omega}_t^g(\vec{\phi}))\tau_{ok}$ *is the covariance between log wages received* ω_{ot}^g *and tasks performed* τ_{ok} *among workers with skill draws* $\vec{\phi}$*.*

In all three expressions in the proposition, the two terms inside the square brackets represent two channels through which changing task prices and race-specific barriers affect conditional wages. The first term captures the direct effect of changing returns within each occupation. A rise in task price β_{kt} will increase the skill return associated with the task; similarly, a reduction in pecuniary task-specific barriers (a less negative $\eta_{kt}^b + \delta_{kt}^b$) will raise the return from performing the task for the group; in contrast, the non-pecuniary task-specific barrier γ_{kt}^b has no direct effect on wages since it is non-pecuniary (hence the zero in the first term within the squared bracket in the last line). The size of this direct effect on wages depends on how much of the task the workers perform in their current occupation, namely the average task content $\overline{\tau}_{kt}^g(\bar{\phi})$ of their work. The second term, on the other hand, captures the indirect effect through changes in occupational sorting. For example, a rise in task return β_{kt} attracts workers skilled in task k to sectors with high τ_{ok}; if these sectors tend to have higher wages – that is, if the co-variance term is positive – then the observed mean (log) wage will increase when workers sort into these occupations.

Note that the non-pecuniary component γ_{kt}^b of task-specific barriers has no direct effect on the racial wage gap unlike the pecuniary component $(\eta_{kt}^b + \delta_{kt}^b)$, even though they affect the sorting in the same way. Based on this observation, we will later use the racial gap in task returns — on which γ_{kt}^b has no direct effect — to separate the non-pecuniary component γ_{kt}^b of the composite racial task barriers from the pecuniary component $\eta_{kt}^b + \delta_{kt}^b$.

Proposition 2 also allows us to analyze the effect of race-neutral and race-specific forces on the aggregate racial wage gap, which is the content of the following key corollary:

Corollary 1. *Let* $\overline{\omega}_t^{agg,g}$ *denote the mean (log) wage across all group* g *workers. The total derivative of the aggregate racial wage gap is given by:*

$$\begin{aligned} d(\overline{\omega}_t^{agg,b} - \overline{\omega}_t^{agg,w}) \approx\ & dA_t^b + \sum_k \left\{ \int \overline{\tau}_{kt}^b(\bar{\phi})\beta_{kt}\, dF_w(\bar{\phi}) \right\} d(\eta_{kt}^b + \delta_{kt}^b) \\ & + \sum_k \left\{ \int \left[\overline{\tau}_{kt}^b(\bar{\phi})\left(\eta_{kt}^b + \delta_{kt}^b\right) + \left(\overline{\tau}_{kt}^b(\bar{\phi}) - \overline{\tau}_{kt}^w(\bar{\phi})\right)\phi_k\right] dF(\bar{\phi}) \right\} d\beta_{kt} \\ & + \text{[Indirect Effect due to Sorting Responses]}. \end{aligned} \tag{7}$$

The indirect effect of sorting responses is small relative to the direct effects for small changes under reasonable parameterizations.[15]

There are two takeaways from this expression. First, a reduction in race-specific barriers ($d(A^b_t) > 0$ and $d(\eta^b_{kt} + \delta^b_{kt}) > 0$) unambiguously reduce the racial wage gap. Second, however, changing task prices ($d\beta_{kt}$) can potentially offset this improvement. More specifically, the second line highlights that increases in returns to tasks where Black workers face high barriers can increase the racial wage gap through two channels. The first term inside the integral on the second line shows that Black workers benefit less from a rising task k return if they, on average, have skill deficits in task k relative to Whites ($\eta^b_{kt} < 0$), or if they are paid as if they had lower skills due to pecuniary discrimination ($\delta^b_{kt} < 0$). The second term shows that differential sorting further amplifies this effect. As highlighted by Proposition 1, the existence of pecuniary and non-pecuniary racial task barriers (η^b_{kt}, δ^b_{kt} and γ^b_{kt}) makes Black workers sort away from occupations that are intensive in the task. If skilled Black workers on average perform less of the task than comparable Whites due to high barriers – that is, if $\overline{\tau}^b_{kt}(\bar{\phi}) - \overline{\tau}^w_{kt}(\bar{\phi}) < 0$ – then they capture even less of the gains from rising task returns. In sum, the corollary implies that, given the existence of the task-specific racial barriers (η^b_{kt}, δ^b_{kt} and γ^b_{kt}), changes in race-neutral task returns (β_{kt}'s) will cause changes in the racial wage gap. Below, we will highlight this implication both through the lens of our estimated model and through model-guided empirical specifications using micro-level data.

3 Racial Differences in Occupational Tasks

In this section, we document racial differences in occupational sorting along task dimensions and highlight how those differences have evolved over time. The above model highlights how these moments can be used to infer underlying task-specific racial barriers.

3.1 Measuring the Task Content of Occupations

We measure the task demands in each occupation using the U.S. Department of Labor's Dictionary of Occupational Titles (DOT) and the Occupational Information Network (O*NET). The DOT was constructed in 1939 to help employment offices match job seekers with job openings. It provides information on the skills used in over 12,000 occupations. The DOT was updated in 1949, 1964, 1977, and 1991, and replaced by the O*NET in 1998.

We focus on four occupational task measures: *Abstract*, *Routine*, *Manual*, and *Contact*. The first three measures are taken exactly from Autor and Dorn (2013) using the DOT data.

[15] Appendix H contains expressions that reflect the indirect effects of sorting responses. But the indirect effects of sorting responses are quantitatively small for small changes. Intuitively, workers are already optimizing so the effect of readjustments in sorting is small; the envelope theorem however does not hold exactly because (i) occupations are discrete and (ii) sorting frictions arise from idiosyncratic occupational preferences.

Below, we provide a brief summary of these measures.[16] The last task measure is new and was created specifically for this paper to help isolate racial discrimination. Building on the insights in Becker (1957), *Contact* measures the extent to which an occupation requires interaction and communication with others within the organization (co-workers) or outside the organization (customers/clients). We conjecture ex-ante and confirm ex-post that the intensity of this task provides a measure of labor market activities where discrimination is likely to be the most salient.

We now briefly summarize our task measures with additional discussion in the appendix:[17]

Abstract: indicates the degree to which the occupation (i) demands analytical flexibility, creativity, reasoning, and generalized problem-solving and (ii) requires complex interpersonal communications such as persuading, selling, and managing others. Occupations with high measures of *Abstract* tasks include accountants, software developers, high school teachers, college professors, judges, various medical professionals, engineers, and managers.

Routine: measures the degree to which the task requires the precise attainment of set standards and/or repetitive manual tasks. Occupations with high measures of *Routine* tasks include secretaries, dental hygienists, bank tellers, machinists, dressmakers, x-ray technology specialists, pilots, drafters, and various manufacturing occupations.

Manual: measures the degree to which the task demands eye, hand, and foot coordination. Occupations with high measures of *Manual* tasks include athletes, police and firefighters, drivers (taxi, bus, truck), skilled construction (e.g., electricians, painters, carpenters), and landscapers/groundskeepers.

Contact: measures the extent to which the job requires the worker to interact and communicate with others. To create our 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.

[16] We download all the task measures used in this paper from David Deming's replication package (Deming (2017a)). We provide a more detailed discussion of all the data sets used in the paper and how variables are defined in Appendix A.

[17] Our goal is to stay as close as possible to the definitions of task measures developed by Autor and Dorn (2013) so as to provide new evidence on the racial differences in these measures. However, in Appendix C, we show that the racial differences in the task content of occupations that we highlight are very similar using alternative *Abstract*, *Routine*, *Manual*, and *Contact* task definitions.

The occupational task measures are available at the 3-digit occupational code level. We use Deming (2017b)'s crosswalk to merge these measures into the other data sets we use. For our descriptive empirical work we use the over 300 harmonized detailed occupation codes from the Census IPUMS data as provided in Deming (2017b). Finally, we convert the task measures into z-score space by taking unweighted differences across occupations. This transforms the units of our task measures into standard deviation differences in the task content of a given occupation relative to all other occupations; an *Abstract* task measure of 2.0 in a given occupation means that occupation has an *Abstract* task requirement that is two standard deviations higher than the average occupation.

Some occupations require all tasks in relatively high intensities. For example, civil engineers have *Abstract*, *Routine*, *Manual*, and *Contact* task intensities of 2.3, 1.2, 0.6, and 0.1, respectively. Some other occupations require all tasks in relatively low intensities. For example, mail carriers have *Abstract*, *Routine*, *Manual*, and *Contact* task intensities of -0.8, -1.5, -0.7, and 0.0, respectively. Other occupations are mixed in their task demands, and the differences in task demands differentiate between occupations. For example, both physicians and retail sales clerks are high in *Contact* intensities, but physicians are also high in *Abstract* task intensities while retail sales clerks are low in *Abstract* task intensities. In Online Appendix Table R1, we report the task requirements of many detailed occupations in z-score units.

Finally, throughout the paper, we follow much of the literature by holding the task content of occupations fixed over time at their 1977 level (e.g., Dorn (2009), Autor and Dorn (2013), and Deming (2017b)). However, recent work has suggested that there are important aggregate shifts over time in the task content of occupations. For example, Atalay et al. (2020) and Cavounidis et al. (2021) document that most occupations are now demanding more *Abstract* tasks and less *Routine* tasks in *absolute* terms. Our estimation strategy is robust to these aggregate shifts in the task content of occupations as we identify and quantify the racial gap in occupational sorting along task dimensions using the *cross-sectional* variation in the task content of occupations. Using the 1977 and the 1991 waves of DOT and the 1998 and the 2021 waves of the O*NET, we find that the task content of occupations is relatively constant over time, up to an aggregate shift. A detailed discussion of these findings can be found in Online Appendix A.[18] Indeed, our key descriptive facts highlighted in this section remain essentially unchanged when we allow for the aggregate task content of occupations to evolve across the DOT samples.

[18]By expressing task contents in z-score units, aggregate shifts in the aggregate task content of jobs are removed from our task measures. Instead, to the extent that those aggregate shifts occur, they will be absorbed into our model estimated β_{kt}'s. In fact, this is exactly the type of race-neutral shifts we are trying to identify in the quantitative analysis we perform in our model. As a result, our model estimates of β_{kt} will capture both the relative change in task returns as well as systematic aggregate shifts in task demands.

3.2 Measuring Occupational Sorting and Wages

To measure time-series and cross-regional racial differences in the task content of occupations and wages, we use data from the decennial U.S. Censuses from 1960 through 2000 and the annual American Community Surveys (ACS) thereafter (Ruggles et al. (2021)). We pool together the micro-data from the annual ACS's between 2010 and 2012 and again between 2016 and 2018. We refer to the former as the "2012 ACS" and the latter as the "2018 ACS". Given this, we have seven separate waves of harmonized data for the years 1960, 1970, 1980, 1990, 2000, 2012, and 2018. Within each wave, we restrict our sample to non-Hispanic White and Black native-born men between the ages of 25 and 54 who do not live in group quarters. We also exclude workers who are self-employed. Finally, we always weight the data using the survey weights provided by the Censuses and the ACS's, respectively.

We measure wages as self-reported annual earnings during the prior year divided by self-reported annual hours worked during the prior year. We only measure wages for individuals who are currently employed working at least 30 hours per week and who reported working at least 48 weeks during the prior year. We treat individuals who are not working as being in the home sector occupation. In some specifications, we control for the worker's age and accumulated years of schooling. All values in the paper are in 2010 dollars. Note, this data and sample underlie the descriptive results on the racial gap in occupational choice discussed in the introduction.

3.3 Trends in Racial "Task Gaps"

To measure the racial gaps in task content of occupations, we begin by estimating the following regression separately for each task in each year using our sample of prime age Black and White men:

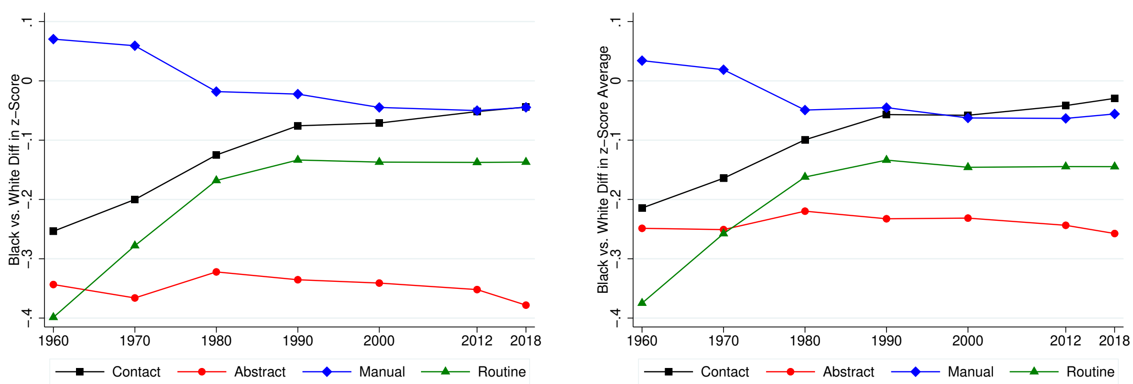
$$\tau_{o(i,t)k} = \alpha_t^k + \lambda_t^k Black_{it} + \sum_{s \neq k} \zeta_{st}^k \tau_{o(i,t)s} + \Gamma_t^k X_{it} + \epsilon_{ikt}, \tag{8}$$

where $\tau_{o(i,t)k}$ is the task content of task k for individual i working in occupation o in period t; $Black_{it}$ is a dummy variable equal to 1 if individual i in year t is a Black man; and X_{it} is a vector of individual 5-year age dummies and five dummies measuring educational attainment (less than high school, high school, some college, a bachelor's degree, or more than a bachelor's degree).[19] To isolate the racial difference in tasks, we also control for the occupational content

[19]Our model does not include the individual's choice of years of schooling prior to entering the labor market. As a result, we estimate the model with data on racial differences in wages and occupational sorting conditional on accumulated years of schooling. As can be seen from the data we provide, conditioning on education mitigates the racial gaps in the level of wages and tasks, but does not meaningful alter the trends. As a result, the key findings of the paper are robust to whether or not we estimate the model using data on racial wage and task gaps conditional on education.

of the other tasks.[20] Our coefficients of interest are the λ_t^k's, which inform the differential propensity of Black men to work in occupations that require task k in year t, holding all other task requirements fixed. We run this regression separately for each year and for each task yielding 28 estimates of λ_t^k. Figure 1 plots these coefficients. Panel A shows the results excluding the X vector of demographic controls while Panel B shows the results including the additional controls. The racial gaps are expressed in z-score units.

Figure 1: Racial Differences in the Task Content of Occupations



Panel A: No Controls

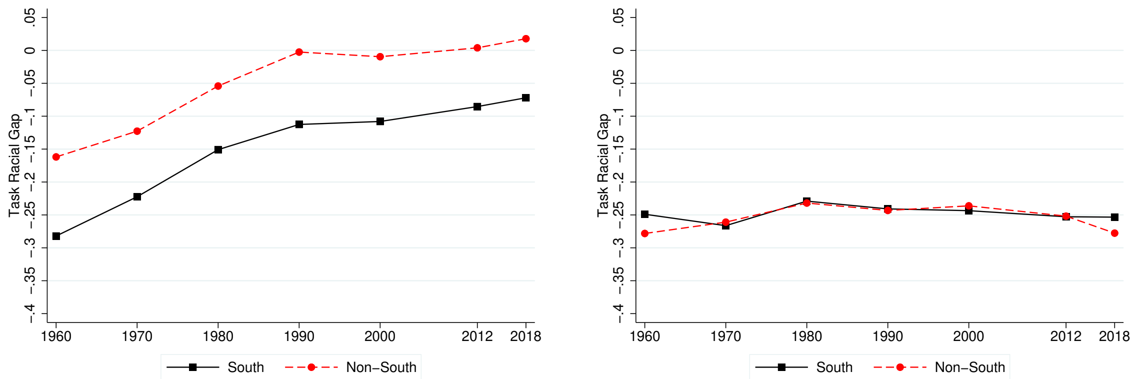
Panel B: With Controls

Notes: Figure shows the estimated λ_t^k's from the regression specified in equation (8). The coefficients measure the racial gap in the task content of occupations. Sample restricted to native-born individuals between the ages of 25 and 54 within the Censuses and ACS years who are not self-employed and who report working more than 30 hours per week. Panel A excludes controls for age and education while Panel B includes those controls. Standard errors on the coefficients (omitted from the figure) had a value of less than 0.01 for all tasks in all years.

Figure 1 shows that both the level difference in racial task gaps in 1960 and the subsequent time series trend differ markedly by task. The differences are especially pronounced when we compare the racial gaps in *Abstract* and *Contact* tasks. In the early 1960s, Black workers were systematically underrepresented both in occupations that required a high intensity of *Abstract* tasks and in occupations that required a high intensity of *Contact* tasks. In terms of magnitudes, Black men in 1960 worked in occupations that required 0.25 standard deviations less *Abstract* tasks and 0.21 standard deviations less *Contact* tasks relative to White men, both conditional on years of schooling. Over the last half a century, however, Black men have made significant progress relative to White men with respect to sorting into occupations that

[20] In Appendix B, we show the raw trends in the $\tau_{o(i,t)k}$'s by year for Black and White men separately. The raw patterns for *Abstract*, *Routine*, and *Manual* tasks for White men are similar to the findings in Autor and Dorn (2013).

Figure 2: Racial Gap in Contact and Abstract Task, By Region



Panel A: Racial *Contact* Gap   Panel B: Racial *Abstract* Gap

Notes: Figure replicates the analysis in Panel B of Figure 1 separately for individuals residing in the South region (solid line) and individuals residing in all other non-South regions (dashed line).

require *Contact* tasks, while they made no progress at all relative to White men with respect to sorting into occupations that require *Abstract* tasks. Whereas the racial gap in *Abstract* tasks remained essentially constant through 2018, the large racial gap in *Contact* tasks that existed in 1960 has all but disappeared by 2018. These findings persists whether or not we control for individual age and education (Panel A vs. Panel B), although the level of the *Abstract* task gap narrows once we control for them.[21]

3.4 Trends in Racial "Task Gaps" By Region

Throughout the paper, we exploit regional variation to learn about the potential causes of the racial task gaps highlighted in Figure 1. In particular, one of the key objectives of the paper is to verify our conjecture that the racial gap in *Contact* tasks reflects the extent of direct racial discrimination in the economy. There is a large body of research documenting that measures of discrimination were initially larger in the South region of the U.S. in the 1960s and 1970s (relative to other regions) and subsequently declined more in the South after 1980 (Charles and Guryan (2008), Bobo et al. (2012)). If the racial gap in sorting into occupations that require *Contact* tasks reflects discrimination, we should expect larger racial *Contact* task gaps in the South in 1960 and a larger narrowing in the racial *Contact* task gap in the South between 1960 and 2018, relative to other regions.

Figure 2 replicates the analysis in Panel B of Figure 1 separately for the individuals in

[21]For much of the paper, we focus our discussion on racial differences in *Abstract* and *Contact* tasks. The racial gap in *Manual* tasks is close to zero in all time periods. The racial gap in *Routine* tasks narrowed up to 1980 and then was relatively constant thereafter.

the Census/ACS data living in the South region and then again for all other regions (which we designate "non-South"). We show the regional patterns for two tasks: *Contact* tasks (Panel A) and *Abstract* tasks (Panel B). Consistent with our conjecture that the racial gap in *Contact* tasks could be a proxy for the extent of direct discrimination in the economy, the racial gap in *Contact* tasks was much larger in the South relative to all other regions in 1960, and the subsequent convergence in *Contact* tasks over the last half century was also greater in the South relative to the other regions. Note, as a point of contrast, the racial gap in *Abstract* tasks was nearly identical in both level and trend between the South and other regions conditional on education. Whatever differences in the racial gap in tasks that exist between the South and other regions are showing up in *Contact* tasks as opposed to in *Abstract* tasks. We will use these patterns later in the paper to further validate our finding that the racial gap in *Contact* tasks provides a good measure of direct discrimination.

3.5 Time Series Changes in Task Returns

As noted in our theoretical model, there is a large value-added from using a task-based approach to understand trends in racial wage gaps when (1) there exist racial task-specific barriers and (2) there are differential trends in task prices over time. To measure how the price of each task has evolved over time, we run the following regressions separately by year for each race group g using the Census/ACS data. These regressions will be used to help pin down the β_{kt}'s in our model.[22] Particularly, we run:

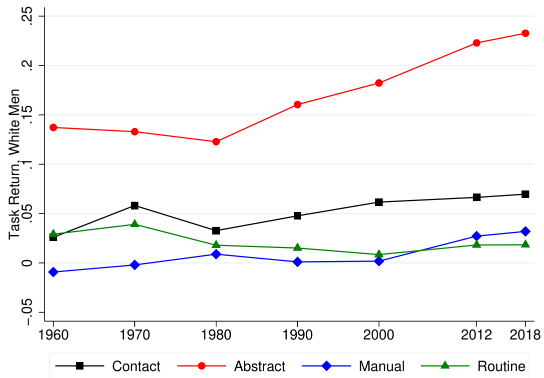
$$\omega_{iot} = \alpha_t^g + \sum_k \tilde{\beta}_{kt}^g \tau_{o(i,t)k} + \Gamma_{kt} X_{it} + \epsilon_{iot}. \tag{9}$$

where ω_{iot} is the log wage of individual i working in occupation o during year t. Our coefficients of interest are the $\tilde{\beta}_{kt}^g$'s, the Mincerian wage premium of task k in year t for group g. For this regression, we use our sample of full-time workers.

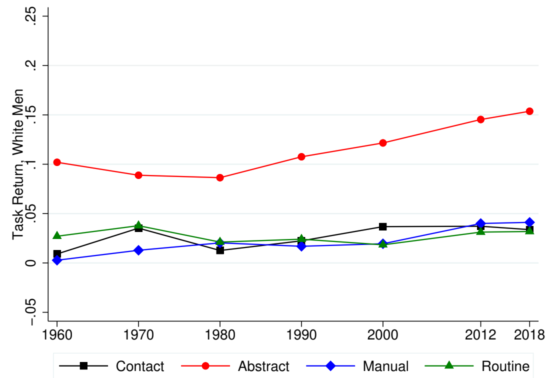
Figure 3 reports estimates of the raw wage premium by task requirement for White men (Panel A), the demographically-adjusted wage premium by task requirement for White men (Panel B) and the demographically-adjusted Black-White gaps in the wage premium by task requirement (Panel C). Three main findings emerge from this figure. First, unconditionally, the average wage premium of *Abstract* tasks for White men was about 10 to 15 percent higher than the return to the other tasks in 1960. Moreover, the relative return of *Abstract* tasks remained relatively constant between 1960 and 1980 and then increased steadily thereafter.

[22]Because of endogenous selection, the estimates of $\tilde{\beta}_{kt}^g$ from equation (9) do not map one-to-one with the β_{kt} counterparts in the model. However, given the model structure, the changes in the $\tilde{\beta}_{kt}^g$'s over time will be useful moments to help estimate the model β_{kt}'s.

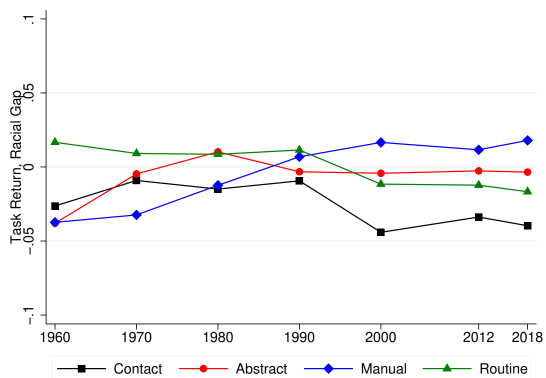
Figure 3: Mincerian Task Premiums, White Men and Racial Gap



Panel A: White Men
No Controls



Panel B: White Men
With Controls



Panel C: Racial Gap
With Controls

Notes: Figure shows the average labor market return to occupational task content for White men without demographic controls (Panel A), for White men with demographic controls (Panel B), and for the difference in returns between White and Black men conditional on demographic controls (Panel C) as estimated in equation (9). All panels use our primary Census/ACS samples with the additional restriction that individuals report working at least 48 weeks during the prior year.

This increase in the return to *Abstract* tasks has received lots of attention in the literature and persists regardless of whether or not one controls for educational dummies (Panel A vs Panel B). Second, in contrast, the wage premiums associated with the other tasks were notably lower for White men in the early 1960s and have not changed much since then. Finally, the racial gaps in the task returns are relatively small and roughly constant over time (Panel C).

3.6 Racial Gap in Wages and Employment Rates

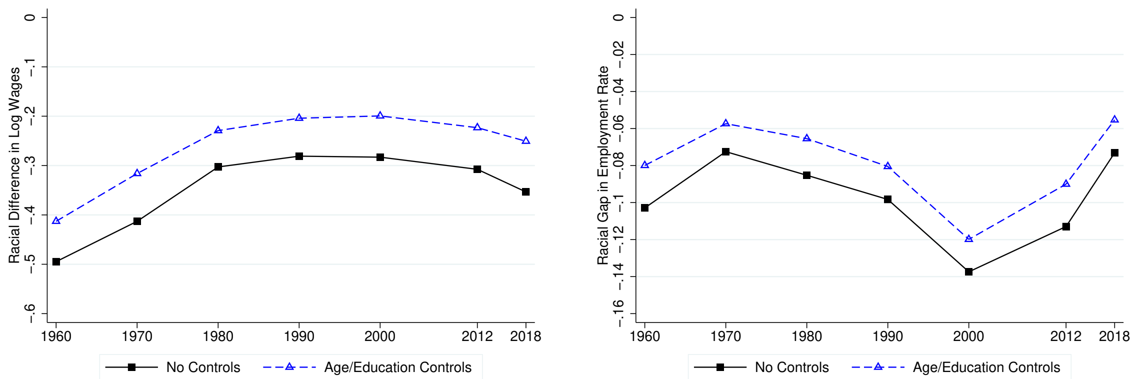
Panel A of Figure 4 shows the mean difference in log wages between Black and White men over the 1960 to 2018 period using data from the U.S. Censuses and the American Community Surveys both with (dashed line) and without (solid line) controlling for age and education. The Black-White wage gap narrowed substantially from the early 1960s through 1980. However, since 1980, the Black-White wage gap has remained essentially constant. The time-series trends in the racial wage gap are nearly identical regardless of whether or not one controls for education; although, the racial wage gap narrows in all periods after controlling for racial differences in education. One of the goals of the paper is to help to explain why the racial wage gap has stopped converging after 1980.

Panel B of Figure 4 shows the racial gap in employment rates unconditionally (solid line) and conditional on age and education (dashed line). The employment rate of Black men declined slightly from 1960 to 2000 relative to White men and then rebounded slightly from 2000 to 2018. Most of our analyses below focus on the periods from 1960 to 1980 and then again from 1980 through 2018. As seen from Panel B, the racial gap in employment rates was roughly the same in 1960, 1980, and 2018. As a result, for these long differences, there was no meaningful change in the racial employment gap that would be confounding our results. However, for completeness, we allow for race-specific preferences for the home sector in our structural model, which we chose to match the differential employment rates across racial groups in each time period conditional on the rest of the model structure. These race-specific preferences for the home sector are not quantitative important for any of our model results; again the reason for this is that the racial gap in employment rates was roughly the same in 1960, 1980 and 2018.

3.7 Robustness of Racial Gap in Task Trends

In this subsection, we briefly mention the variety of alternate specifications we explored to examine the robustness of the above results. All of the details of the robustness exercises can be found in Online Appendix B. One concern that could arise is that the task intensities of occupations proxy the demand for general human capital rather than the demand for specific tasks. To explore this concern, we re-estimated the patterns in the above figures separately segmenting our sample by those with less than a bachelor's degree and those with a bachelor's degree or more. Within both samples, we find that there was a racial convergence in the *Contact* tasks and no racial convergence in *Abstract* between 1960 and 2018; although, we find that the convergence in the *Contact* tasks was slightly stronger among individuals with less than a bachelor's degree. These results highlight that our main findings about the time

Figure 4: Racial Wage and Employment Gaps Over Time



Panel A: Racial Wage Gap

Panel B: Racial Gap in Employment Rates

Notes: Panel A shows the racial gap in log wages with and without controlling for age and education. Panel B shows the racial difference in employment rates with and without controlling for age and education. Data for both panels come from our primary Census/ACS samples.

series patterns in racial task gaps are not being driven by the educational requirement of the occupations associated with the task. Additionally, the appendix shows the trends in the racial gaps in *Abstract* and *Contact* tasks separately for each birth cohort in our sample. The patterns highlight that most of the changes in the racial tasks gaps highlighted in Figure 1 - to the extent that they happen - occur across birth cohorts. Given these results, we are comfortable abstracting from life cycle considerations in both our model and empirical work. Finally, we show that our key patterns in Figure 1 are nearly identical if we exclude low wage workers who are potentially bound by the minimum wage or if we exclude workers in highly unionized sectors.

4 Model Estimation

We estimate the baseline model through minimum distance estimation. Our procedure consists of two steps. First, we estimate the race-neutral aggregate forces in the model from labor market data on White men. Second, given the race-neutral parameters, we estimate the race-specific barriers from the data on differential sorting and pay between Black and White men. Below, we expand on the key components of our estimation procedure.

As discussed above, we use the O*NET and DOT data to discipline the task content of occupations $T_{ok} = (\tau_{o1}, ..., \tau_{oK}) \in \mathcal{R}_+^K$ of occupations. As in our empirical work above, we will have four types of tasks ($K = 4$): *Abstract*, *Contact*, *Routine*, and *Manual*. To maximize power, we aggregate our occupations to the 66 broad occupation categories used in Hsieh et al. (2019) which are based on the 1990 US Census broad occupation sub-headings. Aggregating the data in this way has essentially no effect on the time series patterns of the racial gap in task returns as shown in Figure 1. Appendix Figure R5 shows the analogous patterns from Figure 1 using the broad occupation codes.[23]

The model for White men ($g = w$) is given by equations (3), (4), and (5) along with the normalization that $\delta^w_{kt} = \eta^w_{kt} = \gamma^w_{kt} = A^w_t = 0 \ \forall \ k$ and t. The skill endowment ϕ_{ik} follows a Frechet distribution with shape θ, while the occupational preference ν_{iot} follows a Frechet distribution with shape ψ; we assume the shape parameters ψ and θ to be constant over time and be the same for both racial groups. As we explain below, we set the parameter ψ externally based on empirical estimates of labor supply elasticity. Taking ψ as given, the remaining parameters to be estimated for White men are: time effects A_t in each year; time-invariant occupational returns A_o's for $o = 1, ..., O$; the reservation utility in the home sector A_{Ht} in each year t; the task prices β_{kt}'s for $k = 1, ..., 4$ in each year t; and the Frechet shape parameter θ for the skill distribution. We normalize $A_o = 0$ for $o = 1$.

We estimate the parameter vector $\Theta^w = (\{A_t\}, \{A_o\}, \{A_{Ht}\}, \{\beta_{kt}\}, \theta)$ through 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.[24] Let $\hat{m}^w$ denote the vector of moments in the data, and let $m^w(\Theta^w)$ denote the corresponding moments calculated in the model given parameters Θ_w. Our estimator $\hat{\Theta}^w$ solves

$$\hat{\Theta}^w = \arg\min_{\Theta^w} \left(\hat{m}^w - m^w(\Theta^w)\right)' W^w \left(\hat{m}^w - m^w(\Theta^w)\right), \tag{10}$$

where W^w is a diagonal matrix of weights. We weight moments to adjust for scaling differences and to fit task-related moments (iv) and (v) – which are central to our analysis – more closely than occupation-level moments. We discuss our weighting scheme in detail in Online Appendix I.

While all parameters are estimated jointly, some moments are more instrumental in esti-

[23] A complete discussion of our estimation procedure can be found in Appendix I. In particular, to ensure that the τ's are constant over time, we aggregate the task contents to the broad occupation categories using the detailed occupation weights from 1980 and hold those weights fixed across all years. Also, we discuss how we transform the τ's so they are all positive since $\tau_{o1}, ..., \tau_{oK}$ have to be non-negative in the model.

[24] For the task content of the home sector, we use data from the Census/ACS measuring the individual's last occupation before entering the home sector. We take the average over the years in the sample. However, this normalization plays little role in our main quantitative results given that we allow the A_{Ht}'s to match the actual shares in the home sector for White men in each year.

mating certain parameters. In Online Appendix I, we analyze the sensitivity of our estimators to moments following Andrews et al. (2017). Here, we outline the intuition for why our moments help estimate the parameters. It is hardly surprising that our estimates of occupational returns A_o are sensitive to the average wage and employment in the respective occupations, and likewise that the estimate of the home sector utility A_{Ht} is responsive to the home sector share. So, imagine for a moment that we are provided with A_t, A_o, and A_{Ht}. The key question then is how moments on aggregate task contents and Mincerian task premia provide information to help us infer the model task returns β_{kt} and the Frechet shape parameter θ for skill distributions. In general, for a given θ, raising β_{kt} naturally increases both aggregate task content and Mincerian task premium in the task. But, holding θ fixed, it is generally not possible to fit *both* moments simultaneously just by varying β_{kt}'s. We may however hope to fit both moments more closely by varying θ, as this parameter controls the relative responsiveness of the two moments to β_{kt}.[25] Intuitively, a higher θ makes the tail of the skill distribution thinner and hence makes the task returns less responsive to changes in β_{kt}'s. Put differently, the relative levels of task returns versus task contents give information about the thickness of the tail of the distribution, helping us estimate the shape parameter θ.

As suggested earlier, we set the shape parameter ψ externally to roughly match the empirical estimates of labor supply elasticity. As we show in Online Appendix F, the parameter ψ is closely tied to the elasticity of labor supply in the model. Intuitively, a smaller ψ translates to stronger occupational preferences (which means workers are less responsive to a change in wages) and hence a lower elasticity of labor supply. 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 elasticity estimated in the literature (Chetty et al. (2013)). We show the robustness of our results to alternate values of ψ in Appendix F.

In the second step, with the estimates of race-neutral parameters Θ_w in hand, we estimate the pecuniary and non-pecuniary race-specific barriers. Specifically, in each year, we estimate: the composite of racial skill gap and pecuniary task-based discrimination $\delta^b_{kt} + \eta^b_{kt}$ for each task k; non-pecuniary task-based discrimination γ^b_{kt} for each task k; the level of general (non-task-specific) racial barrier A^b_t; and the gap in the reservation utility in the home sector A^b_{Ht}.

We estimate the parameters year by year. Define the parameter vector $\Theta^b_t = (\{\delta^b_{kt} + \eta^b_{kt}\}, \{\gamma^b_{kt}\}, A^b_t, A^b_{Ht})$ for each t. Just like in the previous step, we estimate Θ^b_t through minimum distance estimation. Specifically, we target (i) the racial gaps in aggregate task contents, (ii) the racial gaps in Mincerian task premiums, (iii) the aggregate wage gap, and (iv) the (log)

[25] Of course, we cannot fit the moments perfectly even in this thought experiment because the model is over-identified. In particular, we assume θ is the same across all tasks and all years. In the actual estimation, A_o's will also adjust to help fit the data better.

racial gap in the home sector shares.[26] Let $\hat{m}_t^b$ denote the vector of these moments in the data in each year t, and let $m_t^b(\Theta^w, \Theta_t^b)$ denote the corresponding moments in the model given parameters (Θ^w, Θ_t^b). Our estimator $\hat{\Theta}_t^b(\hat{\Theta}^w)$ solves

$$\hat{\Theta}_t^b(\hat{\Theta}^w) = \arg\min_{\Theta_t^b} \left(\hat{m}_t^b - m_t^b(\hat{\Theta}^w, \Theta_t^b)\right)' W_t^b \left(\hat{m}_t^b - m_t^b(\hat{\Theta}^w, \Theta_t^b)\right), \tag{11}$$

where W_t^b is a diagonal matrix of weights. In the second step, we match the moments perfectly, so the choice of the weights does not matter.

Our estimation in the second step 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 γ_{kt}^b — based on the observed racial gaps in Mincerian task premiums, noting that non-pecuniary discrimination γ_{kt}^b does not impact labor market returns except through sorting. Last, we attribute any residual aggregate wage gap unexplained by $\delta_{kt}^b + \eta_{kt}^b$, γ_{kt}^b, and A_{Ht}^b to the general non-task-related racial wedge A_t^b.

As we show in Appendix F, our model matches the data on racial gaps in tasks and wages perfectly, but with one exception: *Manual* tasks. Because the empirical wage premium on *Manual* tasks for White men is close to zero, we estimate that $\beta_{Manual,t}$ is zero or near zero for all t. Consequently, the composite racial barriers $(\delta_{kt}^b + \eta_{kt}^b + \gamma_{kt}^b)$ for *Manual* tasks do not meaningfully contribute either to overall racial wage gaps nor to sorting given the model structure. Hence, we focus on estimating the task-specific racial barriers for *Abstract*, *Contact*, and *Routine* tasks only. We thus exclude the racial gaps in aggregate *Manual* task contents and *Manual* wage premiums from the set of moments we target.

Realizing that the quantitative exercises we explore below rely on the functional form assumptions we make for the various distributions from which individuals draw task-specific skills and preferences, we perform a variety of exercises comparing the distributional implications of our model to many non-targeted data moments. We discuss the details of these exercises in Appendix F. In particular, we show that despite only targeting mean racial wage gaps of those men who are working, our model matches very well the relative wages of Black and White men at the median and 90th percentile of their respective wage distributions. Additionally, we show that our model nearly identically replicates racial wage gaps conditional on the task content of occupations as found in the Census/ACS data. Collectively, the fact that our estimated model matches a variety of non-targeted moments well gives us confidence in the quantitative exercises we highlight next.

[26] All the data moments in this step are conditioned on demographics (age and education) as in Section 3.

5 Explaining Racial Differences in Occupational Sorting and Wages

In this section, we show the estimates of the race-neutral driving forces (e.g., task prices) and race-specific driving forces (e.g., racial skill gaps and discrimination) in our structural model. We then show how the various forces contributed to changes in occupation sorting and log wages by race.

5.1 Estimates of Model Driving Forces

We begin by showing estimates of both the race-neutral and race-specific model driving forces. These results are shown in Figure 5 and Table 2.

5.1.1 Estimates of Race-Neutral Task Returns

We first present our estimates of the key race-neutral forces. In particular, the top three rows of Table 2 show the estimated trends in β_{kt}'s for the *Abstract*, *Contact*, and *Routine* task measures. Consistent with the literature, we find that *Abstract* task returns increased sharply after 1980 both in absolute terms and relative to the returns for the other tasks. As we discussed in Section 2.7, our model implies that if Black men face barriers in occupations requiring *Abstract* tasks, a relative increase in the return to *Abstract* tasks will disadvantage Black workers all else equal and, as a result, widen the racial wage gap.

5.1.2 Estimates of Task-Specific Racial Barriers for *Abstract* and *Contact* Tasks

We next present the estimates of the composite task-specific racial barriers, $(\eta^b_{kt} + \delta^b_{kt} + \gamma^b_{kt})$'s. The composite racial barriers comprise the mean task-specific human capital differences (the η^b_{kt}'s) and direct pecuniary and non-pecuniary discrimination measures (the δ^b_{kt}'s and γ^b_{kt}'s) for each task. Given the race-neutral forces, we infer the composite racial barrier $(\eta^b_{kt} + \delta^b_{kt} + \gamma^b_{kt})$ from the racial differences in occupational sorting along each of the k tasks in each year t.

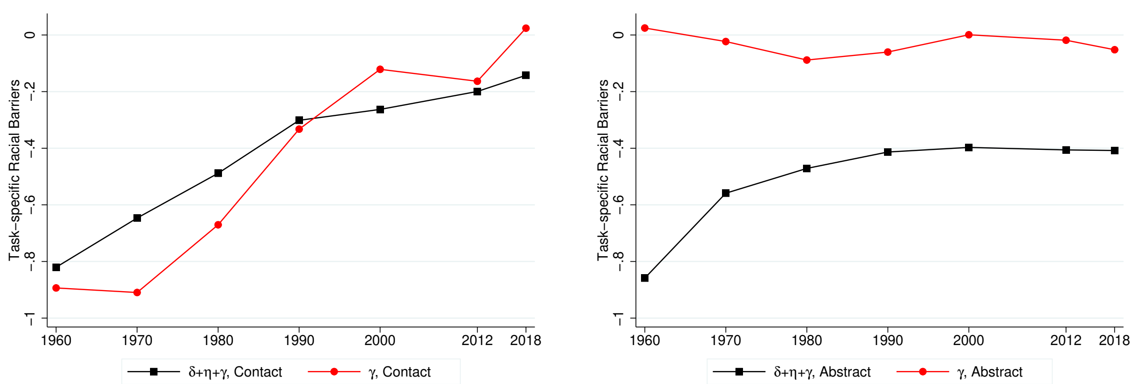
The black lines (with squares) in Panels A and B of Figure 5 show the model estimates of $(\eta^b_{kt} + \delta^b_{kt} + \gamma^b_{kt})$ for *Contact* and *Abstract* tasks, respectively. The figure shows a reduction in the composite term $(\eta^b_{kt} + \delta^b_{kt} + \gamma^b_{kt})$ for both tasks between 1960 and 2018, but the trends differ markedly across the two tasks. On the one hand, most of the decline in the composite racial barrier for *Abstract* tasks occurred prior to 1980, and the racial barrier has persisted since. On the other hand, the composite racial barrier in *Contact* tasks declined consistently throughout the last six decades, reaching a level close to zero by 2018. The latter trend primarily reflects the trend in the racial gap in *Contact* tasks (shown in Figure 1) which almost vanished by

Table 2: Model Estimates of Key Race Neutral and Other Race-Specific Driving Forces

	1960	1970	1980	1990	2000	2012	2018
Race Neutral β_{kt}'s							
$\beta_{Abstract,t}$	0.69	0.71	0.75	0.81	0.88	0.98	1.02
$\beta_{Contact,t}$	0.29	0.35	0.30	0.32	0.32	0.34	0.36
$\beta_{Routine,t}$	0.59	0.60	0.53	0.53	0.52	0.54	0.55
Additional Racial Barriers							
$Routine : (\eta_{kt} + \delta_{kt} + \gamma_{kt})$	-0.87	-0.58	-0.45	-0.39	-0.43	-0.44	-0.47
$Routine : \gamma_{kt}$	-0.74	-0.51	-0.45	-0.35	-0.31	-0.33	-0.28
A_t^b	-0.27	-0.24	-0.18	-0.11	-0.04	-0.06	-0.05
A_{Ht}^b	0.16	0.14	0.16	0.18	0.21	0.14	0.11

Note: Table shows model estimates of the change in aggregate task prices, the β_{kt}'s, as well as the various other race-specific driving forces. The model also estimates $\theta = 3.60$. Key task-specific racial barriers for *Contact* and *Abstract* tasks are graphically illustrated in Figure 5.

Figure 5: Task-Specific Racial Barriers for *Abstract* and *Contact* Tasks



PANEL A: CONTACT   PANEL B: ABSTRACT

Notes: Figure shows 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 (γ_{kt}^b) for *Contact* tasks (Panel A) and *Abstract* tasks (Panel B).

2018. As Proposition 1 highlights, a decline in the composite racial barrier for a task induces the racial gap in occupation sorting along the task dimension to narrow, all else equal.

We then estimate how much of the composite racial task barrier is due to non-pecuniary discrimination (γ_{kt}^b) versus either racial skill gaps or pecuniary discrimination $(\eta_{kt}^b + \delta_{kt}^b)$. Proposition 2 highlights that racial skill gaps and pecuniary discrimination directly affect the racial gaps in task returns, while non-pecuniary discrimination affects them only indirectly through sorting. Based on this insight, we isolate the pecuniary component $(\eta^b_{kt} + \delta^b_{kt})$ of the composite racial barrier from the non-pecuniary component γ^b_{kt} by targeting the racial gaps in task returns, using the model structure to correct for selection as we discuss further below.

The red lines in Figure 5 show our estimates of non-pecuniary discrimination γ^b_{kt}; the difference between the black and red lines gives the estimates of $(\eta^b_{kt}+\delta^b_{kt})$.[27] The figure suggests that the racial barrier in *Contact* tasks is driven primarily by non-pecuniary discrimination γ^b_{kt}; the pecuniary barrier $(\eta^b_{kt}+\delta^b_{kt})$ plays little role in explaining the composite racial *Contact* task gap in any period. It could be that firms explicitly rationed Black men from working in occupations that require interactions with others. Alternatively, it could be that the discrimination from co-workers and customers made these *Contact* jobs undesirable for Black men. In either case, the finding implies that racial skill gaps – which are plausibly pecuniary — do not constitute a meaningful part of the racial barrier in *Contact* tasks. This confirms our ex-ante conjecture that the racial gap in *Contact* tasks would be a good place to look for measures of direct discrimination. In contrast, the estimated γ^b_{kt} for *Abstract* tasks is close to zero in all time periods, implying that essentially of the composite racial gap for *Abstract* tasks is due to a combination of racial skill gaps (η^b_{kt}) and pecuniary discrimination (δ^b_{kt}).[28]

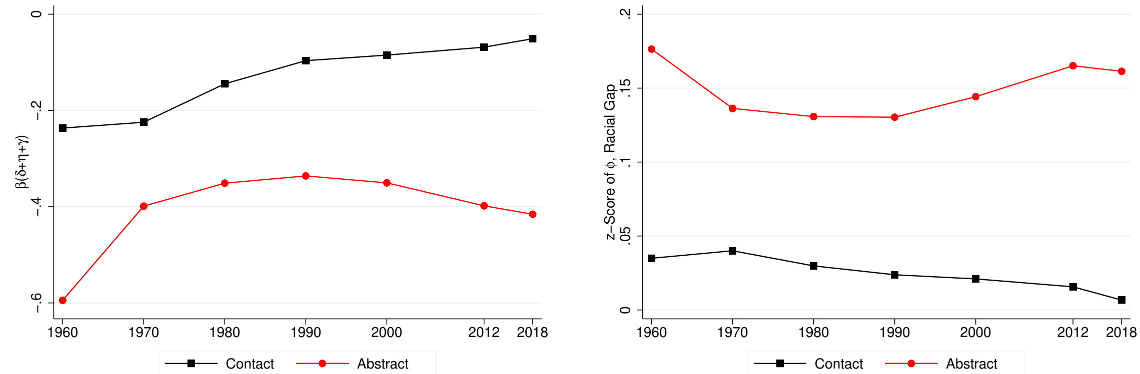
It may initially appear surprising that we find such contrasting trends for pecuniary racial barriers across the two tasks, given that the racial gaps in Mincerian task premiums in the data (shown in Figure 3) are small throughout for both tasks; the reason lies in selection on skills. One implication of our occupational choice model – much as in Hsieh et al. (2019) – is that selection on skills may mask the effect of racial barriers on wages. When Black workers face a high racial barrier in a task, only the high-skilled in the task are likely to sort into occupations that are intensive in the task. This selection tends to reduce the observed racial wage gaps in these occupations, partly masking the negative impact of the racial barriers. Importantly, the magnitude of this selection can differ by task depending on the size of the composite racial barriers and the task price in each task.

Figure 6 highlights that selection plays a large role in *Abstract* tasks but much less so in *Contact* tasks. As seen in equations (3) and (6), the primary determinant of racial differences in selection is the product of the task prices β_{kt} and the racial barriers $(\eta^b_{kt}+\delta^b_{kt}+\gamma^b_{kt})$. We plot this product $\beta_{kt}(\eta^b_{kt} + \delta^b_{kt} + \gamma_{kt})$ in Panel A of the figure. Notice the wedge $\beta_{kt}(\eta^b_{kt} + \delta^b_{kt} + \gamma_{kt})$ is much larger for *Abstract* tasks than for *Contact* tasks. Panel B plots the resulting racial

[27] The estimated racial barriers for *Routine* tasks are shown in Table 2. The composite racial barrier for *Routine* tasks narrowed from 1960 to 1980 and then remained constant thereafter. In recent years, both $(\eta^b_{kt} + \delta^b_{kt})$ and γ^b_{kt} were important in explaining the composite racial barrier.

[28] This model-generated finding is consistent with empirical results based on the National Longitudinal Survey of Youths discussed later in the paper, which show that there are, in fact, large racial gaps in the pre-labor market skills that predict subsequent entry into *Abstract* task-intensive occupations.

Figure 6: Selection into *Abstract* and *Contact* Tasks



Panel A: $\beta_{kt}(\eta^b_{kt} + \delta^b_{kt} + \gamma^b_{kt})$ Panel B: $\bar{\phi}^b_{kt} - \bar{\phi}^w_{kt}$

Notes: Panel A shows the product of the task returns (β_{kt}'s) and the composite pecuniary racial task wedges $(\eta^b_{kt} + \delta^b_{kt} + \eta^b_{kt})$'s for *Contact* and *Abstract* tasks in each time period. Panel B shows the racial gap in selection on latent ϕ_{kt}'s as predicted by the model. Specifically, Panel B shows $\bar{\phi}^b_{kt} - \bar{\phi}^w_{kt}$ for *Contact* and *Abstract* tasks in each time period. The gaps in Panel B are measured in standard deviation differences.

differences in selection by task. Specifically, the panel plots, for each of the tasks, the racial gap in average skill draws $(\bar{\phi}^b_{kt} - \bar{\phi}^w_{kt})$ conditional on being in the same occupation.[29] The ϕ's are expressed in cross-sectional standard deviation units for interpretability. The figure shows that there is little differential selection by race for *Contact* tasks in all periods. For example, in 1960, the average ϕ_{kt} of Black men was only 0.04 standard deviation higher than White men in the same occupation; the gap only declined slightly in the subsequent decades. In contrast, there is much larger differential selection in *Abstract* tasks. In 1960, the average ϕ's for Black men is 0.18 standard deviations higher than White men conditional on occupations.[30]

The weak differential selection by race in *Contact* tasks implies that we can take the small racial gap in Mincerian task premiums for *Contact* tasks (as seen in Panel C of Figure 3) as evidence that pecuniary barriers play little role for *Contact* tasks. Had the pecuniary barriers been the main component of the composite racial barrier in *Contact* tasks, we would have observed a larger racial gap in the Mincerian task premiums in the task given that differential selection does little to offset it. In contrast, for *Abstract* tasks, the combination of the large differential selection by race and the small racial gap in Mincerian task premiums implies that a large pecuniary racial barrier (i.e., racial skill gaps or direct pecuniary discrimination)

[29]Specifically, we regress skill draws ϕ_{ik} of workers estimated from the model on a race dummy and occupation dummies in each period and plot the coefficient on the dummy for Black men.

[30]This does not, however, mean that the actual skill $\phi_{ik} + \eta^g_{kt}$ was higher for Black men conditional on occupations; this figure plots the mean differences in the *race-neutral* part of the skills, ϕ_{ik}.

must underlie the composite racial barrier. Had a large pecuniary racial barrier not offset the differential selection on skills, we would have observed a higher Mincerian task premium for Black men than for White men in *Abstract* tasks. Indeed, in Online Appendix F, we use the estimated model to show that *changes* in selection over time had little impact on the racial gap in the Mincerian task premiums for *Contact* tasks, while it masked a large widening of the racial gap in the Mincerian task premiums for *Abstract* tasks. Collectively, these findings explain the intuition behind our contrasting estimates of γ for *Contact* and *Abstract* tasks.

Admittedly, our decomposition of pecuniary versus non-pecuniary components of the composite racial barriers hinges crucially on the assumption on the extent of differential selection. The extent of differential selection in turn depends on our choice of ψ, the shape parameter for the distribution of idiosyncratic occupational preferences, which controls the amount of sorting friction in the model. In Online Appendix F, we explore alternative values of ψ and demonstrate the robustness of our broad qualitative conclusion that non-pecuniary barriers are the predominant component of the racial task barriers for *Contact* tasks while pecuniary barriers play a large role in *Abstract* tasks.

The main takeaway from this decomposition exercise is that the change in the racial gap in *Contact* tasks gives a good measure of the trend in direct discrimination, as racial skill gaps (which are inherently pecuniary) play a little role in the task. This is in contrast to *Abstract* tasks, where selection forces mask the underlying pecuniary forces despite the similarly small racial gap in Mincerian task premiums. The model-based finding is consistent with empirical results we will present later in the paper where we use cross-state variation to show that the racial gap in *Contact* tasks is strongly correlated with survey-based measures of discrimination.

5.1.3 Estimates of Non-Task-Related Racial Barriers (A_t^b's and A_{Ht}^b's)

Finally, we show our estimates of non-task-related racial barriers, A_t^b's and A_{Ht}^b's. The second to last row of Table 2 shows the estimates of non-task-related pecuniary racial barriers (A_t^b's) for each year. A_t^b's capture any non-task-related forces outside our model that explain the racial wage gap. We estimate a sharp narrowing of A_t^b over the last six decades with much of the decline occurring between 1960 and 2000. This finding is consistent with the existing literature showing that forces such as the Civil Rights Act, the rise in the minimum wage, and changes in the return to general education (unrelated to tasks) were important forces in reducing the racial wage gap during the 1960s, 1970s, 1980s and 1990s.

The last row shows the time series trend in the racial gap in home sector preferences (A_{Ht}^b). To match the empirical fact that the employment rate is lower for Black men than for White men, the model estimates a higher preference for the home sector for Black men in all time periods. However, there is no substantive trend in the differential preferences for the home sector, reflecting the lack of a clear trend in the racial gap in employment rates. All of our quantitative results allow for shifts in the home sector preferences over time but this force does not explain trends in the racial gap in occupational sorting or the racial wage gap over time. Given this, we do not discuss this force any further throughout the rest of the paper.

5.2 Explaining Trends in the Racial Wage Gap

We now use the estimated model to explain the convergence of the racial wage gap between 1960 and 1980 and its stagnation thereafter. Figure 7 quantifies the extent to which the estimated changes in race-neutral and race-specific driving forces impacted the evolution of the racial wage gap over the 1980-2018 period (Panel A) and over the 1960-1980 period (Panel B). For this exercise, we calculate the contribution of each of the model driving forces 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.[31] The exercise allows us to understand how the respective forces – including the rising return to *Abstract* tasks – contributed to the evolution of the racial wage gap over time.

We first consider the evolution of the racial wage gap between 1980 and 2018. The red line (with circles) in Panel A of Figure 7 shows the contribution of the race-neutral driving forces (i.e., the changing β_{kt}'s) to the evolution of the racial wage gap over the period. The exercise shows that changing task returns *widened* the racial wage gap by 7.0 log points over the 1980-2018 period, where the racial wage gap in 1980 was about 22.9 log points. Since $\beta_{Abstract}$ was the only race-neutral force that moved substantially over the period, the rising *Abstract* task return is responsible for essentially all of the adverse race-neutral effects.

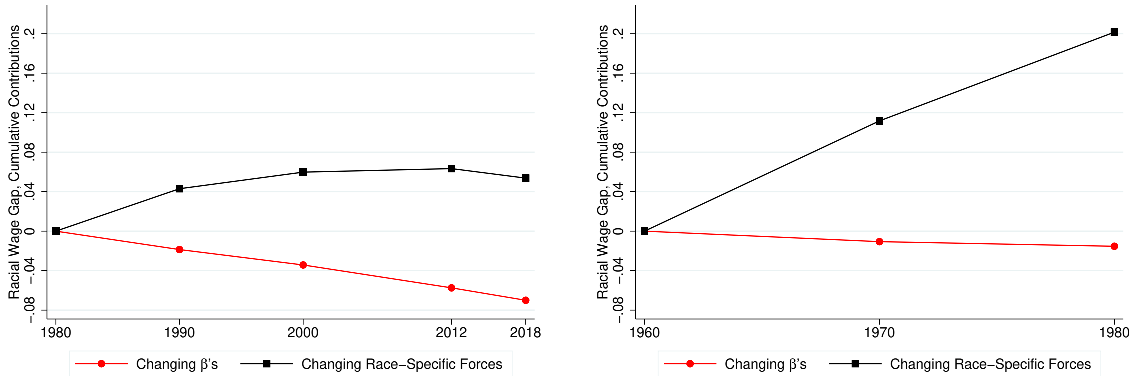
Corollary 1 in Section 2.7 illustrates the two channels through which the rising *Abstract* task return post-1980 widened the racial wage gap. First, since the racial task barriers in *Abstract* tasks had deterred many Black workers from entering occupations with high *Abstract* task requirements in the first place, Black workers tended to be left out from the relative increase in wages in these occupations. Second, even for Black workers who had sorted into *Abstract*-intensive occupations, the large *pecuniary* racial barriers $\delta^b_{kt} + \eta^b_{kt}$ in *Abstract* tasks acted like a tax on the rising task returns and reduced the wage gains for those Black workers relative to their White counterparts in the same occupations. Intuitively, if Black workers have lower *Abstract* skills on average, or if *pecuniary* discrimination makes them paid as if they have lower *Abstract* skills, then they benefit less from the rising *Abstract* task price.[32]

The rising *Abstract* task returns masked the labor market progress that Black men would

[31] See Online Appendix I for the formal derivations of this quantitative exercise.

[32] Quantitatively, the first channel accounts for about 45% of the total contribution of changing task prices on the racial wage gap, while the second channel accounts for about 37%; the remaining 18% is the indirect effect through responses in occupational sorting.

Figure 7: Cumulative Contributions to Changes in Racial Wage Gaps Over Time



Panel A: 1980-2018 Panel B: 1960-1980

Notes: Figure shows cumulative contributions of race-neutral forces (β_{kt}'s) and race-specific forces (δ^b_{kt}'s, η^b_{kt}'s, γ^b_{kt}'s, and A^b_t's) to the evolution of the racial wage gaps over the 1980 to 2018 period (Panel A) and over the 1960 to 1980 period (Panel B).

have otherwise made due to declining race-specific barriers. The black line (with squares) in Panel A of the figure isolates the contribution of the composite race-specific forces (the δ^b_{kt}'s, η^b_{kt}'s, γ^b_{kt}'s, and A^b_t's) to the evolution of the racial wage gap during the 1980-2018 period. The figure implies that the decline in the race-specific forces actually *narrowed* the racial wage gap by 5.4 log points during this period. Essentially all of the convergence was driven by a decline in the general non-task-related racial barrier, A^b_t. This is because task-specific non-pecuniary discrimination γ^b_{kt} — which has been the predominant force driving the decline in the racial task barriers since 1980 — affects the racial wage gap only indirectly through sorting. Since workers are already optimizing, the effects of such resorting tend to be relatively small.

In sum, the model suggests that the racial wage gap has remained relatively constant since 1980 because of two offsetting effects. On the one hand, a combination of declining discrimination and a narrowing of racial skill gaps reduced the racial wage gap between 1980 and 2018 by about 5.4 percentage points. On the other hand, the increasing return to *Abstract* tasks widened the gap by about 7.0 percentage points during the same period. Because of the persistent barriers in *Abstract* tasks, Black workers were not able to capture as much of the gains from the increasing returns in these activities. These two sets of forces have roughly offset each other and kept the racial wage gap relatively unchanged between 1980 and 2018.

Between 1960 and 1980, in contrast, changes in task returns had little effect on the evolution of the racial wage gap, as Panel B of Figure 7 shows. Instead, the racial wage gap was entirely driven during this period by an improvement in the race-specific driving forces. The effects of the improvement in the race-specific forces between 1960 and 1980 were four times larger than the wage effects between 1980 and 2018 (0.20 vs 0.05). Of these effects over the 1960-1980 period, about half (0.09 of the 0.20 change) was due to improving non-task-related forces A_t^b's while the other half was due to improving task-specific forces $(\eta_{kt}^b + \delta_{kt}^b + \gamma_{kt}^b)$'s. Our findings are therefore consistent with the large literature showing that (potentially non-task-related) forces such as the Civil Rights Act and rising minimum wage had a large effect on improving the relative labor market outcomes of Black men during the 1960s and 1970s.

5.3 Explaining Trends in the Racial Gap in *Abstract* Tasks

Empirically, the racial gap in occupational sorting along the *Abstract* task dimension widened a little between 1980 and 2018 (Figure 1). Yet, we estimate that the composite racial barrier for *Abstract* tasks declined slightly during this period (Figure 5). How is it that the racial *Abstract* task gap widened despite a decline in the composite racial *Abstract* task barrier? This is because, when the *Abstract* task price rose post-1980, the existing racial barriers prevented Black men from sorting into *Abstract*-intensive occupations as much as White men did. As shown in Proposition 1, changes in *Abstract* task prices dampen the occupational sorting response when composite racial task barriers exist.

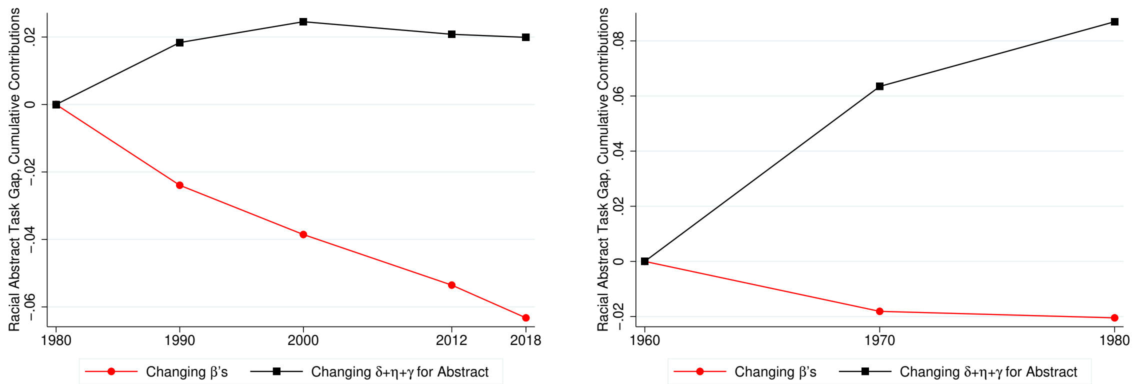
Figure 8 highlights the respective importance of the race-neutral and race-specific forces over the 1980-2018 period (Panel A) and the 1960-1980 period (Panel B) by performing the same decomposition exercise as above with the racial gap in *Abstract* tasks. Panel A shows that increasing *Abstract* task prices post-1980 disproportionally drew White men into occupations requiring *Abstract* tasks (the red line). This masked the effect of declining racial task barriers (the black line). In contrast, Panel B shows that the narrowing of the racial gap in *Abstract* tasks between 1960 and 1980 was entirely due to a decline in the composite racial task barrier for *Abstract* tasks. As above, this is because the relative task prices did not change much.[33]

6 Theory Guided Empirical Work: Isolating Changing Racial Barriers in Micro-data

The analysis in the prior section relies heavily on the model structure. However, the model structure does provide a road map to empirical researchers looking either (i) to uncover the importance of changing task prices in explaining the racial wage gap or (ii) to isolate the importance of changing race-specific driving forces in explaining the racial wage gap. In particular, the model suggests – as highlighted in Corollary 1 – that one must control for

[33] Although it not shown in the figure, essentially all of the convergence in the racial gap in *Contact* tasks during both sub-periods was due to the declining composite racial barrier for *Contact* tasks.

Figure 8: Cumulative Contributions to Changes in *Abstract* Task Gap



Panel A: 1980-2018 Panel B: 1960-1980

Notes: Figure shows cumulative contributions of changing task returns (β_{kt}'s) and changing composite racial *Abstract* task barriers ($(\delta^b_{kt}+\eta^b_{kt}+\gamma^b_{kt})$'s) to the evolution of the racial gap in *Abstract* tasks over the 1980 to 2018 period (Panel A) and over the 1960 to 1980 period (Panel B).

changes in the return to different tasks when analyzing the evolution of Black-White wage differences over time. We now use both our base Census/ACS samples and panel data from the 1979 and 1997 waves of National Longitudinal Survey of Youths (NLSY) to implement a set of theory-guided empirical specifications.

6.1 Isolating the Importance of Changing Task Prices on the Racial Wage Gap in Micro Data

We begin by using the Census/ACS samples to isolate in a reduced form way the importance of changing task prices from 1980 to 2018 in causing the racial wage gap to *increase* during that period, all else equal. In particular, we estimate the following equation on our base sample of White men aged 25-54 who are working full time:

$$\omega^w_{iot} = \alpha_t + \sum_k \tilde{\beta}^w_{kt}\tau_{o(i,t)k} + \sum_E \chi^w_{Et} D^E_{it} + \epsilon^w_{iot} \tag{12}$$

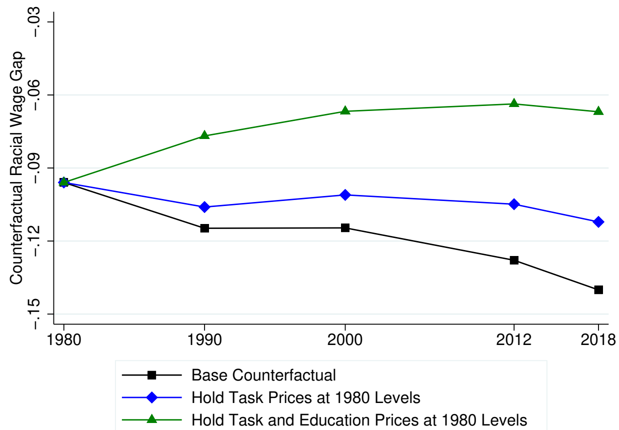
As above, the variable ω^w_{iot} is the log wage of White man i working in occupation o in time t while $\tau_{o(i,t)k}$ is the task content of occupation o in which individual i works during year t. Finally, D^E_{it} is a vector of the same five education dummies representing the education level of individual i in year t as discussed in Panel B of Figure 1. We estimate this regression separately for each Census/ACS year between 1980 and 2018. Notice, we allow the constant (the α_t's), the coefficients representing the task prices for White men (the $\tilde{\beta}^w_{kt}$'s), and the coefficients representing the education returns for White men (the χ^w_{Et}'s) to vary over time. By including both task and education controls, we assess the relative importance of changing task prices separately from changing education returns.

We then use the estimated regression coefficients for the time dummies (α_t's), the task prices (the $\tilde{\beta}^w_{kt}$'s) and the education returns (the χ^w_{Et}'s) from the above regression that uses a sample of only White male workers to project the log hourly wages of both White and Black workers, denoted $\hat{\omega}^w_{iot}$ and $\hat{\omega}^b_{iot}$, respectively. For White men, $\hat{\omega}^w_{iot}$ is just the fitted value of log wages from the above estimation regression given the task content of the occupation where they work and their education level in each year. For Black men, $\hat{\omega}^b_{iot}$ is the predicted log wages that Black men working in occupation o with education level E would earn in year t if they faced the same task prices and education returns as White men. We then compute the racial wage gap under this counterfactual ($\hat{\omega}^b_{iot}$ - $\hat{\omega}^w_{iot}$) and plot the gap over time.

This counterfactual shuts down any of the direct effects of pecuniary discrimination on the racial wage gap because we project the Black wages using the estimated wage equation for White men. In other words, we are imposing that the task prices, educational returns, and the regression constant are the same between Black and White men. Thus, the only reason log wages under this counterfactual would systematically differ between White and Black men is either because Black men work in different jobs or because they have different education levels relative to White men. Moreover, the only reason that the racial wage gap would have changed over time in this counterfactual is that either (i) task prices and educational returns changed over time given that Black and White men initially (in 1980) sorted into different occupations or had different levels of education or (2) the occupational sorting and education levels of Black men relative to White men changed over time. The black line (with squares) in Figure 9 shows this counterfactual. Under this counterfactual, the racial wage gap in 1980 would have been about 9.5 log points. This is much smaller than the empirical racial wage gap of about 23 log points.

Importantly, the black line in Figure 9 is consistent with the predictions of the model in that if we abstract from changes in discrimination over time, the racial wage gap would have widened substantially between 1980 and 2018. The magnitude of the change in the reduced form counterfactual using the Census/ACS data (the black line in Figure 9) is very similar to the model estimate of the contribution of the changing task prices on the racial wage gap (the red line in Figure 7). Specifically, the model estimates that changing task prices increased the racial wage gap by about 7 log points over the period; the ACS/Census counterfactual implies that ignoring the direct effect of changing discrimination, the racial wage gap would have increased by about 5 log points during the same time period. We prefer the model estimates as the model allows changing task prices to endogenously change

Figure 9: Counterfactual Racial Wage Gaps Over Time, Census/ACS Data



Notes: Figure shows a variety of reduced form empirical counterfactuals for the racial wage gaps using data from the Census/ACS. Sample is otherwise the same as those used in Figure 3. The counterfactual uses data from White men to project log wages onto the task requirements of the their occupation and a series of education dummies separately for each year as highlighted in equation (12). We use the regression coefficients from this equation to predict the log wages of both Black and White men. The black line (with squares) shows the baseline counterfactual racial wage gap from this exercise. The other two counterfactual racial wage gaps hold various coefficients fixed at their 1980 level.

occupational sorting. Nonetheless, the reduced-form analysis with micro-data reassures us that our model-based findings are not an artifact of the model structure.

Figure 9 shows two other counterfactuals that shed light on the importance of changing task prices and changing education returns in explaining changes in the racial wage gap over time. First, we recalculate our reduced-form counterfactual racial wage gap using equation (12) now fixing all task prices (the $\tilde{\beta}^w_{kt}$'s) at 1980 levels for all t. This counterfactual – shown with the blue line (with diamonds) – allows us to assess what would happen to the racial wage gap ignoring the direct effect of changing discrimination and also holding the return to tasks fixed over time using the Census/ACS data. Under this counterfactual, the racial wage gap would have been roughly constant, implying that changing task prices were the primary drivers of the widening of the racial wage gap under the first counterfactual where we allowed task prices to evolve as in the data. Although not shown in the figure, all of the difference between the blue and black lines was due to the changing return to *Abstract* tasks.

The green line (with triangles) in Figure 9 shows one final counterfactual where we hold all task prices (the β^w_{kt}'s) and the educational returns (the χ^w_{Et}) constant at their 1980 levels. There are two takeaways from this counterfactual that we want to highlight. First, under this counterfactual, the racial wage gap narrowed by about 3 log points between 1980 and 2018. Since we control for both changing task and educational returns, the only reason that the racial wage gap would narrow in this counterfactual is if Black men are converging in either their educational attainment or the task content of their occupations relative to White men. Thus, the reduction in the racial gap under this counterfactual quantifies the wage effect of Black men converging in their occupational sorting and in their educational attainment during this period. Second, by comparing the green, blue, and black lines, one can assess the relative importance of changing task prices versus changing education returns on the racial wage gap. As seen from the figure, the effect of changing task returns on the racial wage gap is roughly the same order of magnitude as changing educational returns on the racial wage gap. Bayer and Charles (2018)'s seminal work highlighted the importance of changing education returns on the racial wage gap. Our framework highlights that changing task returns (conditional on education) is an additional mechanism affecting the racial wage gap that is on the same order of magnitude as changing education returns.

6.2 Isolating the Importance of Changing Race-Specific Factors on the Racial Wage Gap in Micro Data

In the previous subsection, we showed how researchers can use insights from the model to infer the importance of changing task prices on the racial wage gap from reduced-form micro-data. In this subsection, we show how one can use panel micro-data to isolate the importance of changing race-specific forces on the racial wage gap. To do so, we bring in additional data from the National Longitudinal Survey of Youths (NLSY).[34]

The 1979 and 1997 NLSY waves are representative surveys of 12,686 and 8,984 individuals, respectively, who were between the ages of 15 and 22 years old in 1979 or 13-17 years old in 1997 when they were first surveyed. Respondents from each cohort were subsequently surveyed either annually or bi-annually every year since the initial survey. When using the NLSY data, we restrict the main sample to Black and White non-self-employed men 25 years of age and older. As in with the Census/ACS data, we measure wages as annual earnings divided by annual hours worked. A full discussion of the NLSY data – including details of sample restrictions and variable construction – can be found in Online Appendix A.

We use the panel component of the NSLY combining respondents from both the 1979 and 1997 NLSY cohorts to run the following regression:

$$\omega^g_{iot} = \alpha^0 + \alpha^1_t D_t Black_i + \sum_k \alpha^2_{kt} D_t \bar{\tau}_{o(i,t)k} + \Gamma X_{it} + \mu_i + \epsilon_{it} \tag{13}$$

where again ω^g_{iot} is the log wage of individual i from the NLSY in period t and $\bar{\tau}_{o(i,t)k}$'s are

[34] See, U.S. Department of Labor, Bureau of Labor Statistics (2019a) and U.S. Department of Labor, Bureau of Labor Statistics (2019b).

the average task contents of the occupations where individual i worked during their life. We compute the $\bar{\tau}_{o(i,t)k}$'s for each individual for our four task measures (*Abstract*, *Contact*, *Routine* and *Manual*). The average task measures are more representative of the individual's task content of their occupation than focusing on only one year.

Guided by the findings of our structural model, we estimate relative Black progress in log wages after *controlling for changing task returns* that can mask this progress. Specifically, when we control for the average task content of an individual's occupation, we allow the labor market returns to the tasks – the regression coefficients on the $\bar{\tau}_{o(i,t)k}$'s – to evolve over time; note that the individual average task measures are interacted with time dummies (the D_t's). According to our structural model, controlling for time varying task returns will allow researchers to isolate the importance of changes in race-specific driving forces in explaining changes in racial wage gaps over time.

In addition to controlling for changing task returns, our empirical specification also controls for omitted time-invariant factors – such as unmeasured skills that are constant within an individual over time – by including individual fixed effects (μ_i). Hence, we identify the year-specific race dummies (the α_t^1's) by exploiting within-individual changes over time. We also include demographic controls (X_{it}) consisting of (i) age and education dummies again interacted with time dummies and (ii) the interaction of age and $Black_i$. The former set of controls will control for time-varying education returns. In terms of estimation, we segment the NLSY into four-year periods: 1980-1989, 1990-1999, 2000-2009, and 2010-2018. We set the 1980-1989 period to be the benchmark year group so all other differences in the racial wage gap over time are relative to the 1980-1989 period.

The results from the regressions are shown in Table 3. To illuminate the effects of including various controls, we show in column 1 the evolution of racial wage gaps in the NLSY controlling only for the individual fixed effects and our standard demographic controls interacted with time dummies. As with the patterns in the Census/ACS data, the racial wage gap in the NLSY has been roughly constant between the early 1980s and the late 2010s even conditional on individual fixed effects and controlling for time-varying returns to education.

Once we control for the rising return to *Abstract* tasks over time, however, we find a stronger convergence in racial wage gaps post-1980. Specifically, in column 2, we control for time-varying returns to just *Abstract* tasks. In this column, we find a narrowing of the racial wage gap relative to the 1980s of about 4 log points in the 1990s and about 9 log points in the 2000s and 2010s. The results are nearly identical when we additionally control for time-varying returns for the other tasks (column 3). As suggested by our model, conditioning out the effects of time-varying task returns – the rising return to *Abstract* task in particular – unveils the convergence in the racial wage gap due to changing race-specific factors. The

Table 3: The Evolution of Racial Wage Gaps Over Time in the NLSY: The Importance of Controlling for Time-Varying Task Returns

	(1)	(2)	(3)
Racial Wage Gap: 1990s	0.018	0.036	0.037
	(0.019)	(0.019)	(0.019)
Racial Wage Gap: 2000s	0.045	0.089	0.093
	(0.031)	(0.031)	(0.031)
Racial Wage Gap: 2010s	0.041	0.089	0.092
	(0.038)	(0.039)	(0.039)
Demographic Controls * Year Dummies	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes
Abstract Task Content * Year Dummies	No	Yes	Yes
Other Task Content* Year Dummies	No	No	Yes

Notes: Table shows the evolution of the racial log wage gap over time in the NLSY data with various sets of controls. Data uses the pooled sample of the NLSY 1979 and 1997 waves. Sample restricted to Black and White men between the ages of 25 and 54. Robust standard errors clustered at the individual level shown in parentheses.

magnitude of the convergence we estimate in the NLSY between 1980 and 2018 once properly controlling for the changing returns to tasks (column 3 of Table 3) is broadly similar to the magnitude we estimate from our structural model (Panel A of Figure 7).

7 Racial Gap in *Contact* Tasks as a Measure of Discrimination

One of the key findings from our structural model is that the racial gap in Contact tasks is primarily driven by non-pecuniary discrimination. In this section, we exploit cross-regional variation to provide additional evidence that the racial gap in *Contact* tasks is indeed a good proxy for direct discrimination. In particular, we perform two distinct exercises. First, we re-estimate our model separately for different regions of the United States. We show our model also does well in explaining the differential evolution of the racial wage gap across regions. Second, we show that the racial gap in *Contact* tasks at the state level correlates strongly with existing survey measures of direct discrimination at the state level.

7.1 Model Estimates for the South and non-South Regions

We start by estimating our model separately using Census/ACS microdata for the South region and then again for all other regions (Non-South). As noted in Section 3, there is a large amount of empirical evidence concluding that there is more direct discrimination against Black men in the South region than in the Non-South region. Using data from the General Social Survey (GSS), we confirm that residents of the South expressed more discriminatory preferences in the 1970s compared to residents in the Non-South and those discriminatory preferences subsequently declined more in the South during the 1970-2000 period. For example, during the 1970s, over 50% of White respondents from the GSS who resided in the South reported that they were against interracial marriage. In contrast, only about 30% of White respondents from the GSS who resided in other regions reported being against interracial marriage in the 1970s. By the early 2000s, about 20% of White residents in the South and only about 10% of White residents in the Non-South still reported being against interracial marriage.

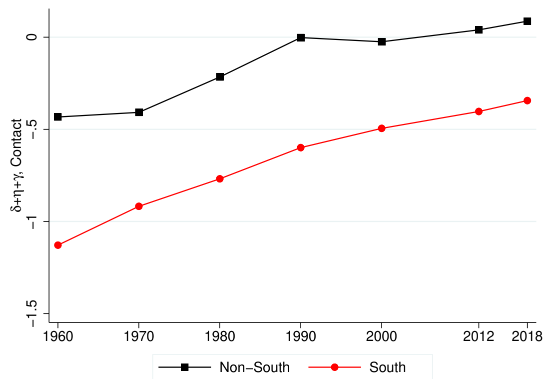
If the racial gap in *Contact* tasks is indeed a good measure of direct discrimination, we expect the composite racial barrier we estimate in the model to satisfy the following three properties in line with the survey-based measures of direct discrimination. First, the estimated composite racial barrier for *Contact* tasks must be much larger in the South than in the Non-South in all periods. Second, the decline in the estimated barriers in *Contact* tasks between the 1960s and today should be larger in the South than in other regions. Finally, substantive racial barriers in *Contact* tasks must be remaining in the South even today.

Figure 10 confirms these three predictions. The figure presents results from re-estimating our key results shown in Figures 5 and 7 separately for the South and then again for the three other Non-South regions combined.[35] First, consistent with survey measures of direct discrimination being higher in the South in all periods, Panel A shows that our model estimate of the composite racial barrier $(\eta_{kt} + \delta_{kt} + \gamma_{kt})$ for *Contact* tasks is much larger in the South relative to all other regions in all time periods between 1960 and 2018. Second, the decline in the composite friction for *Contact* tasks was much larger in the South over this period. Last, as of 2018, we find that the estimated barrier for *Contact* tasks in the South is still large while the estimated barrier in other regions is close to zero. Though not shown in the figure, we also find that essentially all of the composite $(\eta_{kt} + \delta_{kt} + \gamma_{kt})$ for *Contact* tasks - both in levels and trends - was due to non-pecuniary discrimination γ_{kt} in both regions, mirroring the results in Figure 5 for the aggregate economy.

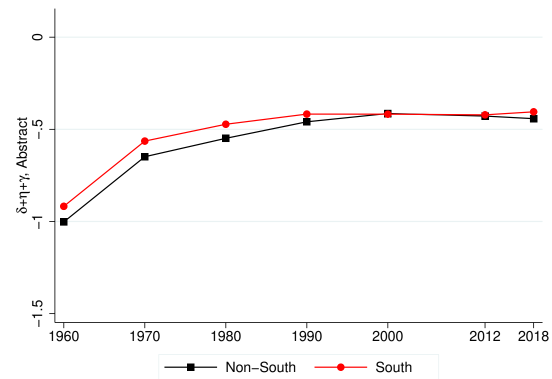
As a point of contrast, Panel B of the figure also shows the estimated composite racial

[35] When estimating race-specific driving forces in the separate region models, we take the race-neutral parameters $\hat{\Theta}^w$ estimated from the all-region model; this ensures the size of estimated racial barriers is comparable across regions, though it imposes that the β_{kt}'s are common across the regions in each period.

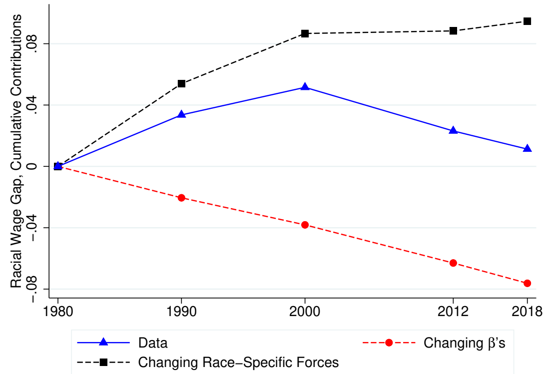
Figure 10: Racial Barriers and their Contributions to Racial Wage Gap, South vs Non-South



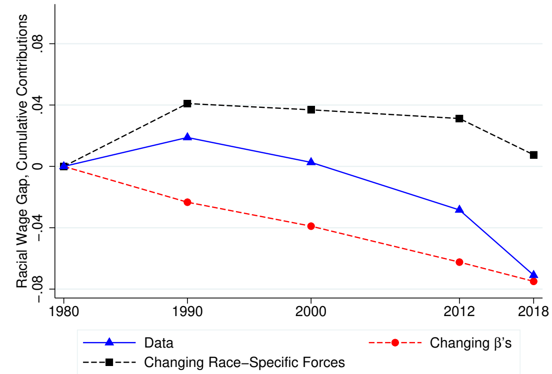
Panel A: $\eta^b_{kt} + \delta^b_{kt} + \gamma^b_{kt}$, Contact



Panel B: $\eta^b_{kt} + \delta^b_{kt} + \gamma^b_{kt}$, Abstract



Panel C: Contributions, South



Panel D: Contributions, Non-South

Notes: Panels A and B show model estimates of the composite racial barrier in the South and Non-South regions for *Contact* and *Abstract* tasks, respectively. Panels C and D show the empirical racial wage gap (solid blue line) for the South and Non-South regions, respectively. The two other dashed lines in the panels show the estimated contributions of changing task prices (dashed red line) and changing race-specific forces (dashed black line) to the evolution of the racial wage gap over time in each region.

barrier for *Abstract* tasks. We estimate that the size of the barrier was nearly identical between the South and Non-South in all time periods. In other words, it is not that occupational choice differences, per se, identify measures of racial discrimination. Instead, consistent with our ex-ante conjecture, it is the racial gap in occupations requiring *Contact* tasks - where workers have to interact with others - that is a good proxy for direct measures of discrimination.

The comparison of regional estimates provides further validation of the model prediction regarding how the rising *Abstract* task price impacts the racial wage gap. Recall that we explained the stagnation of the racial wage gap post-1980 in the aggregate economy with two offsetting forces. On the one hand, the decline in measures of discrimination tends to narrow the racial wage gap. On the other hand, the rise in *Abstract* task price tends to widen the gap. If the above mechanism actually underlies the evolution of the racial wage gap, we then should expect the racial wage gap to *widen* more in the Non-South regions during this time period, because the first effect should be larger in the South while the second effect should be roughly similar across regions. Panels C and D validate these predictions. Specifically, the solid blue lines in the two panels show the actual racial wage gap data from the Census/ACS for the South and Non-South regions. They show that, empirically, the racial wage gap (conditional on education) *narrowed* by about 1 log point in the South and *increased* by about 7 log points in the Non-South between 1980 and 2018.

Panels C and D of Figure 10 also provide the decomposition of forces underlying these regional trends as we did in Figure 7 for the aggregate economy. The dashed red line (with circles) and the dotted black line (with squares) in each panel show, respectively, the estimated contributions of changing task prices (the β_{kt}'s) and changing race-specific barriers (the η^b_{kt}'s, δ^b_{kt}'s, γ^b_{kt}'s, and $A^b_{k=t}$'s) to the evolution of the racial wage gap in each region. The result confirms that the racial wage gap widened in the Non-South since 1980 because *Abstract* task price increased during this period with no offsetting improvements in discrimination. The exercise shows that our model explains not only the trends in the aggregate economy but also the cross-region differences in the evolution of the racial wage gap during this time period.

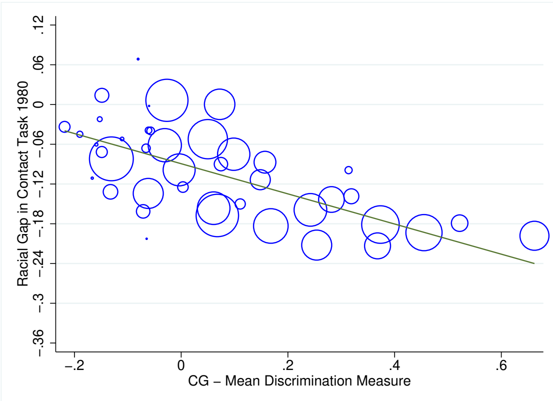
7.2 Racial Gap in *Contact* Tasks and Survey Measures of Direct Discrimination, Cross-State Variation

Our last empirical exercise provides the strongest support for our model finding that the racial gap in *Contact* tasks is a good proxy for direct discrimination. In particular, we compare state-level racial gaps in *Contact* tasks with state-level survey-based measures of direct discrimination. Charles and Guryan (2008) (henceforth CG) use confidential location data from the General Social Survey (GSS) conducted during the 1970s through the early 1990s to make survey-based measures of taste-based discrimination for each state. The GSS asked a nationally representative sample dozens of questions eliciting potential prejudice against Blacks.[36] Focusing on a sample of White individuals, CG create measures of state-level prejudice against Blacks.[37] Their measure is standardized with higher values indicating larger

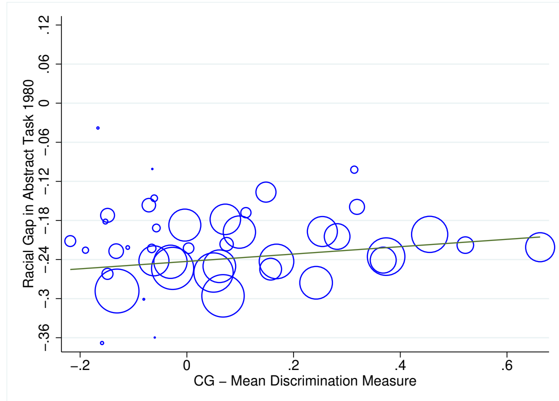
[36] For example, respondents were asked how they would feel if a close relative was planning to marry someone who was Black, whether they would ever vote for a Black president, or whether they were in favor of laws restricting interracial marriage. We used the latter question in our GSS analysis discussed above.

[37] Charles and Guryan (2008) produce measures of the average level of discrimination in the state as well as the discriminatory preferences of the marginal individual. We use their average measure in our work below, but the results are very similar using their marginal measure. We thank Kerwin Charles for sending us a text file with their computed average and marginal state level discrimination measures. See pages 782-786 of Charles and Guryan (2008) for how these variables were constructed.

Figure 11: Racial Gaps in *Contact* and *Abstract* Tasks vs Survey Measures of Taste-Based Discrimination, State Level Variation



Panel A: Contact Tasks



Panel B: Abstract Tasks

Notes: Figure shows state-level conditional racial gaps in the *Contact* task content of jobs (Panel A) and the *Abstract* task content of jobs (Panel B) against the Charles-Guryan (CG) mean measures of state level prejudice. Racial gaps in the task content of jobs measured using the 1980 U.S. Census. Task gaps are conditioned on age and education. Each observation is a U.S. state with the size of circle measuring the number of Black individuals in the state in the 1980 Census.

levels of direct discrimination among Whites within the state.

Panel A of Figure 11 correlates measures of racial gaps in the *Contact* tasks for each state with the CG state-level direct discrimination measures. Specifically, for each state, we measure the conditional race gap in *Contact* tasks using the specification in equation (8). Given the GSS was conducted in the mid-1970s through the early 1990s, we map the CG measures to our 1980 data. As seen from the figure, there is a strong correlation between the state-level racial gaps in the *Contact* tasks in 1980 and the CG measure of state-level discrimination; a simple regression line through the scatter plot yields a slope coefficient of -0.23 (standard error = 0.04) and an R-squared of 0.44. That is, states with high survey-based measures of direct discrimination are systematically the states with a larger racial gap in *Contact* tasks.

Panel B, on the other hand, illustrates the relationship between the CG measures of discrimination and state-level gaps in *Abstract* tasks. As seen from this figure, the relationship between survey-based measures of direct discrimination and the racial gap in *Abstract* tasks is much weaker than the relationship with the racial gap in *Contact* tasks. In particular, the simple regression line has a slope coefficient of 0.06 (standard error = 0.03) and an R-squared of 0.06. Consistent with our model findings, racial gaps in *Contact* tasks are much more predictive of direct measures of discrimination than racial gaps in *Abstract* tasks. Collectively, these results provide further support for our finding that changes in the racial gaps in *Contact* tasks are informative measures of changing direct discrimination.

8 Additional Results

One of the key findings of the paper is that the composite racial barrier in *Contact* tasks is driven by non-pecuniary discrimination while the composite racial barrier in *Abstract* tasks is driven by a combination of a racial gap in skills and pecuniary discrimination. In this section, we discuss an additional set of exercises we performed to isolate the importance of racial skill gaps in the estimated composite racial barriers in *Contact* and *Abstract* tasks. While we only briefly summarize these results here, Appendix E provides the full details of the exercises.

To measure the extent to which Black and White men systematically differ in the skills needed to perform *Contact* and *Abstract* 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. First, 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. Second, we use measures of the Rotter Locus of Control Scale and the Rosenberg Self-Esteem Scale (for the 1979 cohort) and respondent self-reports of their conscientiousness (for the 1997 cohort) to create our non-cognitive skill measures. Finally, for the 1979 cohort, we use self-reported measures of sociability in childhood and sociability in adulthood to create a measure of social skills. For the 1997 cohort, 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. In particular, all of our skill measures and definitions are exactly the same as the skill measures used in Deming (2017b).

With this data, we first perform two descriptive exercises. First, using data for White men, we find that measures of cognitive test scores when the individual is a teenager strongly predict entry into occupations requiring *Abstract* tasks when they are adults. Conversely, we find that measures of social skills when young strongly predict entry into occupations that require *Contact* tasks when adults. Second, we show that the racial gap in cognitive skills was very large for the 1979 cohort (about 1 standard deviation difference). While the cognitive test score gap between Black and White men declined between the 1979 and 1997 cohorts, it was still quite large for workers entering the labor market during the 2000s (about 0.6 standard deviation difference). As a point of contrast, there was no essentially no racial gap in social skills in either period.

We then develop a procedure that combines the NLSY skill measures with our model estimates to parse out how much of the pecuniary racial barrier for each task is due to racial skill gaps (the η_{kt}^{b}'s) and how much is due to pecuniary discrimination (the δ_{kt}^{b}'s). In particular, for each of our task measures, our model gives the average skills of individuals working in each occupation separately for White and Black men. To convert the NLSY skill measures into model units, we exploit cross-occupational variation and regress the average task-specific skills for White men working in an occupation in a given time period from the model on the occupational averages of cognitive, non-cognitive and social skills for White men in each time period from the NLSY data. The coefficients from these regressions serve as the weights that convert NLSY skill measures into model units. Using these coefficients and the actual NLSY measures of skills for both White and Black men, we predict the racial gap in skills (expressed in model units) for each task in each occupation for each time period. We then choose the η_{kt}^{b}'s that match the predicted racial skills gaps. We thereby decompose the composite pecuniary barrier $\eta_{kt}^{b} + \delta_{kt}^{b}$ in each task into its component parts.

The procedure provides additional support for one of our key model findings, namely that the composite racial gap in *Contact* task was primarily driven by direct discrimination. In particular, we find that very little of the composite racial barrier in *Contact* tasks is driven by racial skill gaps. The finding stems from the fact that social skills are the most important of the NLSY skill measures in predicting entry into occupations that require *Contact* tasks for White men, but there was no racial gap in social skills within the NLSY data.

Conversely, we find that much of the composite racial barrier in *Abstract* tasks in each period was due to racial skill gaps. This result is driven by the fact that cognitive skills strongly predict entry into *Abstract* tasks and the NLSY data finds a large racial gap in AFQT test scores. Moreover, this procedure finds that about half of the narrowing of the composite racial gap in *Abstract* tasks during our sample period is due to a narrowing of the racial skill gap. This result stems from the fact that the racial gap in cognitive skills within the NLSY data narrowed over time. As we discuss in Online Appendix E, there is likely more noise with our decomposition method for *Abstract* task both due to differential measurement error by race in the mapping of AFQT scores to labor market outcomes (as highlighted in Neal (2006) and Rodgers and Spriggs (1996)) and due to the potential of statistical discrimination. However, even with that caveat, the results are broadly consistent with the baseline model finding that racial skill gaps are not important for explaining the racial gap in *Contact* tasks but are likely very important for explaining the racial gap in *Abstract* tasks.

9 Conclusion

In this paper, we developed a task-based model with race-specific barriers to explain differences in occupational sorting and wages between Black and White men over the last sixty years in the United States. We then estimate the model using micro-data from the U.S. Censuses and the American Community Survey. We use the model to infer the task-specific racial barriers faced by Black men and how those barriers differentially changed over time for each task. Finally, we use the model to assess how changing task prices and changing race-specific barriers affected both racial gaps in occupational sorting and wages over time.

The paper presents two important quantitative results. First, we document that the racial gap in occupational sorting along *Abstract* tasks remained constant over the last six decades while occupational sorting along *Contact* tasks converged during this period. Our paper establishes that the declining racial gap in *Contact* tasks between 1960 and 2018 is a good proxy for declining discrimination during this period. We motivated the introduction of this novel task measure by conjecturing *ex-ante* that occupations which require many interactions with others are more likely to be susceptible to direct discrimination; our model and data work confirm this conjecture *ex-post*. Specifically, our model suggests that the racial gap in *Contact* tasks is driven by non-pecuniary discrimination on the part of employers and customers. To further provide evidence for this conclusion, we document that state-level racial gaps in *Contact* tasks correlate strongly with state-level survey measures of direct discrimination.

Second, our paper provides an explanation for the large reduction in the Black-White wage gap during the 1960s and 1970s and its stagnation thereafter. In particular, we find that the stagnation of the racial wage gap post-1980 is a product of two offsetting effects. On the one hand, reductions in race-specific barriers narrowed the racial wage gap, all else equal. On the other hand, the rising return to *Abstract* tasks during the same period disadvantaged Blacks relative to Whites and widened the racial wage gap. The magnitude of these two effects were roughly similar resulting in a roughly constant racial wage gap post-1980. In contrast, we find that the relative wage gains of Black men during the 1960-1980 period stemmed solely from declining race-specific barriers; relative task prices were roughly stable over this earlier period and hence they hardly affected the racial wage gap.

The observation that changing race-neutral forces such as rising *Abstract* task returns can impact the racial wage gap in presence of task-specific racial barriers provides a road map to empirical researchers looking to uncover changing race-specific factors in micro data. In particular, we show that it is critical to control for changing task returns when attempting to identify how race-specific barriers have changed over time. We implement the empirical specification suggested by our theory and show that the reduced-form estimates are similar to what we find in our structural model.

While there was a narrowing in the racial gap in skills associated with *Abstract* tasks over time, we estimate that large racial *Abstract* skill gaps remain. We want to stress that these racial gaps in skills themselves are endogenous products of discrimination. Current and past levels of discrimination are almost certainly responsible for Black-White differences in *Abstract* skills. Such caveats should be kept in mind when trying to segment current racial wage gaps into parts due to direct discrimination and parts due to differences in market skills. To the extent that we identify discrimination as being an important barrier to labor market equality between Black and White workers, these estimates should be viewed as a lower bound given that the racial skill gaps themselves stem from past racial prejudice. However, we also wish to stress that regardless of the reason for the racial *Abstract* skill gaps that remain, the existence of such gaps imply that changes in *Abstract* task returns can have meaningful effects on the evolution of racial wage gaps. Our paper highlights that it is becoming even more important today to equalize opportunities in early childhood to close the racial *Abstract* skill gap given that the return to *Abstract* skills has been rising over time.

References

Acemoglu, Daron and David Autor, "Skills, Tasks and Technologies: Implications for Employment and Earnings," in "Handbook of Labor Economics, Volume 4. Amsterdam: Elsevier-North" 2011, pp. 1043–1171.

_ **and Pascual Restrepo**, "Tasks, Automation, and the Rise in US Wage Inequality," Working Paper 28920, National Bureau of Economic Research June 2021.

Aigner, Dennis J. and Glen G. Cain, "Statistical Theories of Discrimination in Labor Markets," *ILR Review*, 1977, *30* (2), 175–187.

Altonji, Joseph G. and Rebecca M. Blank, "Chapter 48 Race and gender in the labor market," in "in," Vol. 3 of *Handbook of Labor Economics*, Elsevier, 1999, pp. 3143 – 3259.

_ **, Prashant Bharadwaj, and Fabian Lange**, "Changes in the Characteristics of American Youth: Implications for Adult Outcomes," *Journal of Labor Economics*, 2012, *30* (4), 783–828.

Andrews, Isaiah, Matthew Gentzkow, and Jesse M. Shapiro, "Measuring the Sensitivity of Parameter Estimates to Estimation Moments*," *The Quarterly Journal of Economics*, November 2017, *132* (4), 1553–1592.

Atalay, Enghin, Phai Phongthiengtham, Sebastian Sotelo, and Daniel Tannenbaum, "The Evolution of Work in the United States," *American Economic Journal: Applied Economics*, April 2020, *12* (2), 1–34.

Autor, David, "David Autor's Data Archive," 2024. MIT Economics, Cambridge, MA https://economics.mit.edu/people/faculty/david-h-autor/data-archive.

_ **and David Dorn**, "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market," *American Economic Review*, August 2013, *103* (5), 1553–97.

_ **and Michael Handel**, "Putting Tasks to the Test: Human Capital, Job Tasks, and Wages," *Journal of Labor Economics*, 2013, *31* (S1), S59 – S96.

_ **, Frank Levy, and Richard Murnane**, "The Skill Content of Recent Technological Change: An Empirical Exploration," *The Quarterly Journal of Economics*, 2003, *118*, 1279–1333.

Bayer, Patrick and Kerwin Kofi Charles, "Divergent Paths: A New Perspective on Earnings Differences Between Black and White Men Since 1940," *The Quarterly Journal of Economics*, 01 2018, *133* (3), 1459–1501.

Becker, Gary, *The Economics of Discrimination*, University of Chicago Press, 1957.

Black, Dan, "Discrimination in an Equilibrium Search Model," *Journal of Labor Economics*, 1995, *13* (2), 309–33.

Bobo, Lawrence D., Camille Z. Charles, Maria Krysan, and Alicia D. Simmons, "The Real Record on Racial Attitudes," in Peter V. Marsden, ed., *Peter V. Marsden, ed.*, Vol. 1 of *Social Trends in American Life: Findings from the General Social Survey Since 1972*, Princeton University Press, 2012, pp. 38–83.

Bohren, J. Aislinn, Peter Hull, and Alex Imas, "Systemic Discrimination: Theory and Measurement," Working Paper 29820, National Bureau of Economic Research March 2022.

Card, David and Alan B. Krueger, "School Quality and Black-White Relative Earnings: A Direct Assessment," *The Quarterly Journal of Economics*, 1992, *107* (1), 151–200.

Cavounidis, Costas, Vittoria Dicandia, Kevin Lang, and Raghav Malhotra, "The Evolution of Skill Use Within and Between Jobs," Working Paper 29302, National Bureau of Economic Research September 2021.

Chandra, Amitabh, "Labor-Market Dropouts and the Racial Wage Gap: 1940-1990," *American Economic Review*, May 2000, *90* (2), 333–338.

Charles, Kerwin Kofi and Jonathan Guryan, "Prejudice and Wages: An Empirical Assessment of Becker's The Economics of Discrimination," *Journal of Political Economy*, 2008, *116* (5), 773–809.

Chay, Kenneth Y, Jonathan Guryan, and Bhashkar Mazumder, "Birth Cohort and the Black-White Achievement Gap: The Roles of Access and Health Soon After Birth," Working Paper 15078, National Bureau of Economic Research June 2009.

Chetty, Raj, Adam Guren, Dayanand Manoli, and Andrea Weber, "Does Indivisible Labor Explain the Difference between Micro and Macro Elasticities? A Meta-Analysis of Extensive Margin Elasticities," *NBER Macroeconomics Annual*, 2013, *27* (1), 1 – 56.

_ , Nathaniel Hendren, Maggie R Jones, and Sonya R Porter, "Race and Economic Opportunity in the United States: an Intergenerational Perspective," *The Quarterly Journal of Economics*, 5 2020, *135* (2), 711–783.

Coate, Stephen and Glenn C. Loury, "Will Affirmative-Action Policies Eliminate Negative Stereotypes?," *The American Economic Review*, 1993, *83* (5), 1220–1240.

Deming, David, "Replication Data for: The Growing Importance of Social Skills in the Labor Market," 2017. Havard Dataverse, Version 1, https://doi.org/10.7910/DVN/CYPKZH.

Deming, David J., "The Growing Importance of Social Skills in the Labor Market," *Quarterly Journal of Economics*, 2017, *132* (4), 1593–1640.

Derenoncourt, Ellora and Claire Montialoux, "Minimum Wages and Racial Inequality," *The Quarterly Journal of Economics*, 09 2020, *136* (1), 169–228.

Donohue, John J. and James Heckman, "Continuous Versus Episodic Change: The Impact of Civil Rights Policy on the Economic Status of Blacks," *Journal of Economic Literature*, 1991, *29* (4), 1603–1643.

Dorn, David, "Essays on Inequality, Spaital Interaction, and the Demand for Skill," Dissertation, University of St. Gallen Dissertation 2009.

Freeman, Richard B., "Changes in the Labor Market for Black Americans, 1948-72," *Brookings Papers on Economic Activity*, 1973, *20*, 67–120.

Heckman, James J. and Tim Kautz, "Hard Evidence on Soft Skills," *Labour Economics*, 2012, *19*, 451–464.

_ , Jora Stixrud, and Sergio Urzua, "The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior," *Journal of Labor economics*, 2006, *24* (3), 411–482.

_ , Thomas M. Lyons, and Petra E. Todd, "Understanding Black-White Wage Differentials, 1960-1990," *American Economic Review*, May 2000, *90* (2), 344–349.

Hsieh, Chang-Tai, Erik Hurst, Charles Jones, and Peter Klenow, "The Allocation of Talent and U.S. Economic Growth," *Econometrica*, 2019, *87* (5), 1439–1474.

Hurst, Erik, Yona Rubinstein, and Kazuatsu Shimizu, "Replication package for: Task-Based Discrimination," 2024. American Economic Association [publisher]. Accessed at (add link when provided).

Juhn, Chinhui, K. Murphy, and B. Pierce, "Accounting for the Slowdown in Black-White Wage Convergence," in Marvin Kosters, ed., *Workers and Their Wages: Changing Patterns in the United States*, American Enterprise Institute, 1991.

Kline, Patrick M, Evan K Rose, and Christopher R Walters, "Systemic Discrimination Among Large U.S. Employers," Working Paper 29053, National Bureau of Economic Research July 2021.

Levine, Ross and Yona Rubinstein, "Smart and illicit: who becomes an entrepreneur and do they earn more?," *The Quarterly Journal of Economics*, 2017, *132* (2), 963–1018.

Neal, Derek, "Chapter 9 Why Has Black–White Skill Convergence Stopped?," in E. Hanushek and F. Welch, eds., *E. Hanushek and F. Welch, eds.*, Vol. 1 of *Handbook of the Economics of Education*, Elsevier, 2006, pp. 511–576.

_ and William Johnson, "The Role of Premarket Factors in Black-White Wage Differences," *Journal of Political Economy*, 1996, *104* (5), 869–895.

Rodgers, William and William Spriggs, "What does the AFQT really measure: Race, wages, schooling and the AFQT score," *The Review of Black Political Economy*, 06 1996, *24*, 13–46.

Rosenfeld, Jake and Meredith Kleykamp, "Organized Labor and Racial Wage Inequality in the United States," *American Journal of Sociology*, 2012, *117* (5), 1460–1502.

Roy, A. D., "Some Thoughts on the Distribution of Earnings," *Oxford Economic Papers*, 06 1951, *3* (2), 135–146.

Ruggles, Steven, Sarah Flood, Sophia Foster, Ronald Goeken, Jose Pacas, Megan Schouweiler, and Matthew Sobek, "IPUMS USA," 2021. Minneapolis, MN, Version 11.0, https://doi.org/10.18128/D010.V11.0.

Smith, James P. and Finis R. Welch, "Black Economic Progress After Myrdal," *Journal of Economic Literature*, 1989, *27* (2), 519–564.

U.S. Department of Labor, Bureau of Labor Statistics, "National Longitudinal Survey of Youth 1979 Cohort, Rounds 1-27," 2019. Distributed by the Center for Human Resource Research (CHRR), The Ohio State University, Columbus, OH, https://www.nlsinfo.org/content/cohorts/nlsy79/get-data.

_ , "National Longitudinal Survey of Youth 1997 Cohort, Rounds 1-18," 2019. Distributed by the Center for Human Resource Research (CHRR), The Ohio State University, Columbus, OH, https://www.bls.gov/nls/nlsy97.htm.

U.S. Department of Labor, Employment and Training Administration, "O*NET-SOC Taxonomy," 2023. Used under the CC BY 4.0 license, www.onetcenter.org/taxonomy.html.

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 β_{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

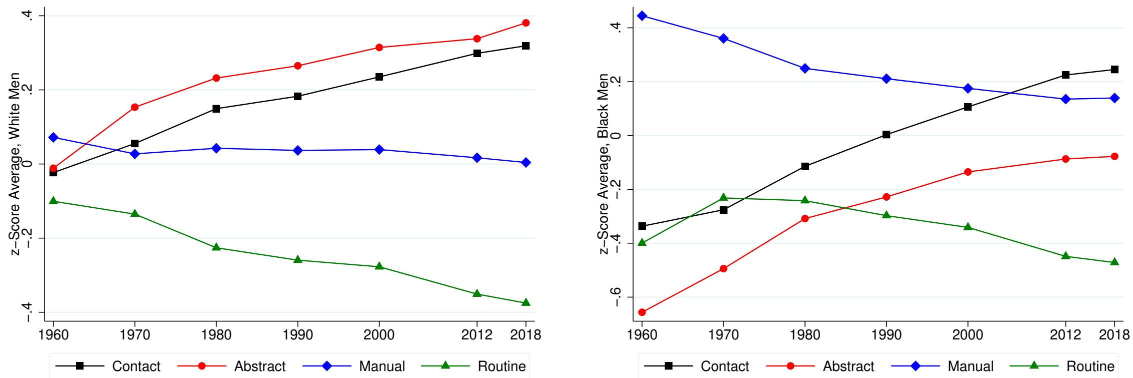
In this section of the appendix, we show the robustness of our results with respect to the time series trends in racial task gaps. We start by showing the raw task trends separately for Black and White men (in the main text, we only show the racial gaps). We then show the robustness of the racial task 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 (ξ^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:

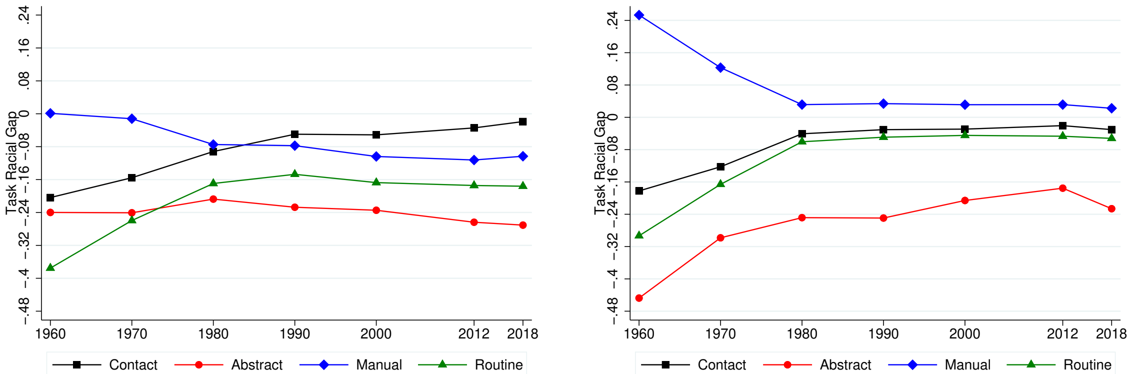
$$\tau^k_{iogt} = \sum_t \xi^g_{kt} D_t + \epsilon_{iogt} \tag{R1}$$

where, as in the main text, τ^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, ξ^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).

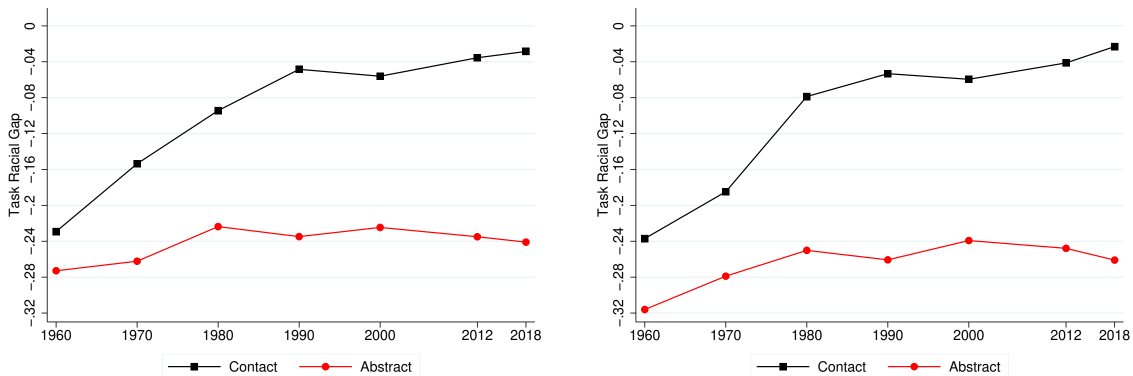
Appendix B.3 Racial Task Gaps, Excluding Low Wage Workers and Excluding Highly Unionized Industries

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

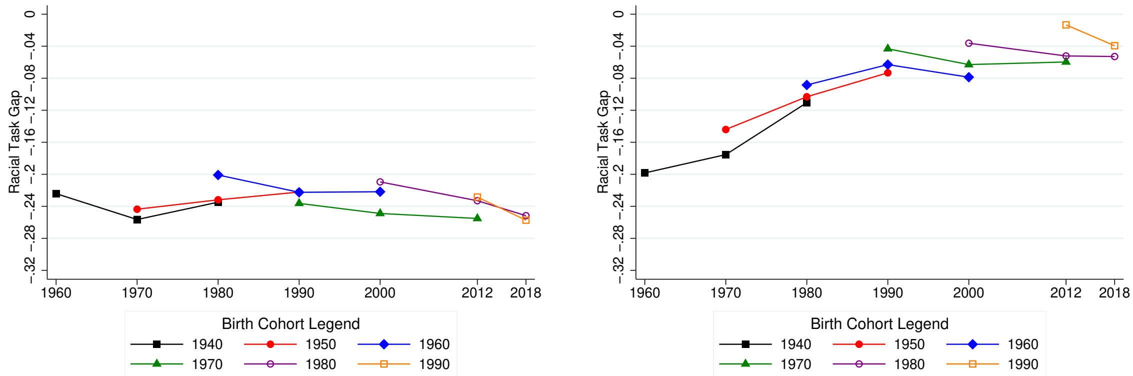
Notes: Figure re-estimates Panel B of Figure 1 of the main text separately exclusing those in the bottom 10 percent of the wage distribution (Panel A) and excluding those working in highly unionized sectors (Panel B). We classify the highly unionized sectors as those workers whose industry is Construction,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



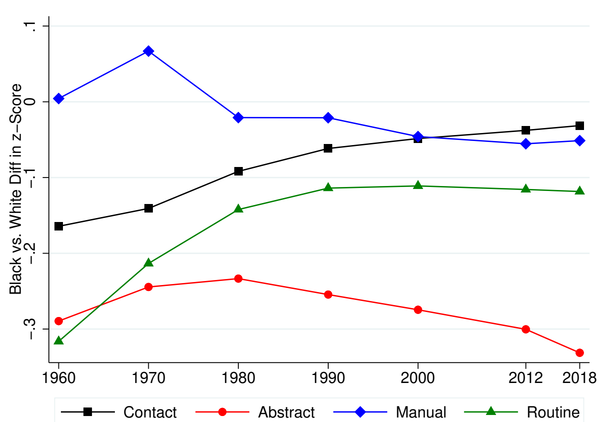
PANEL A: *Abstract* TASK   PANEL B: CONTACT TASK

Notes: Figure shows the estimated λ_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

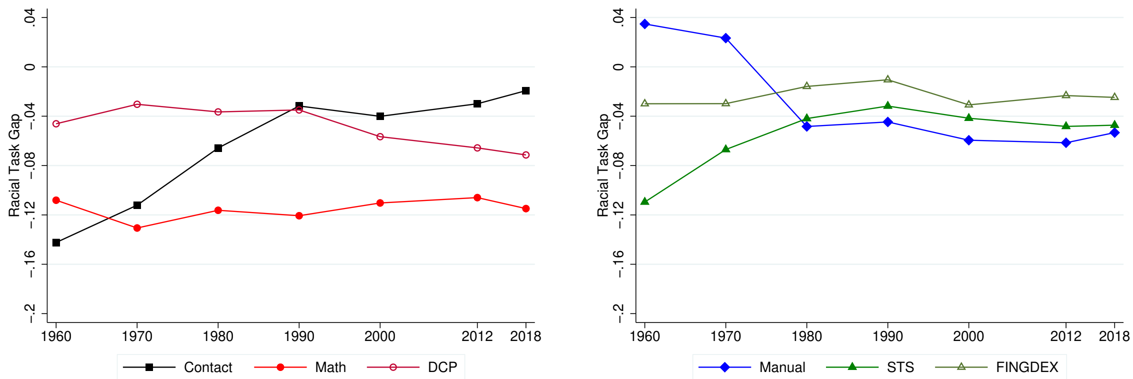
In this section of the appendix, we explore the robustness of our results to alternate definitions for our four task measures. We begin by disaggregating our current task measures into their separate task components. We then explore the racial gaps in alternate definitions of our four main task categories.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

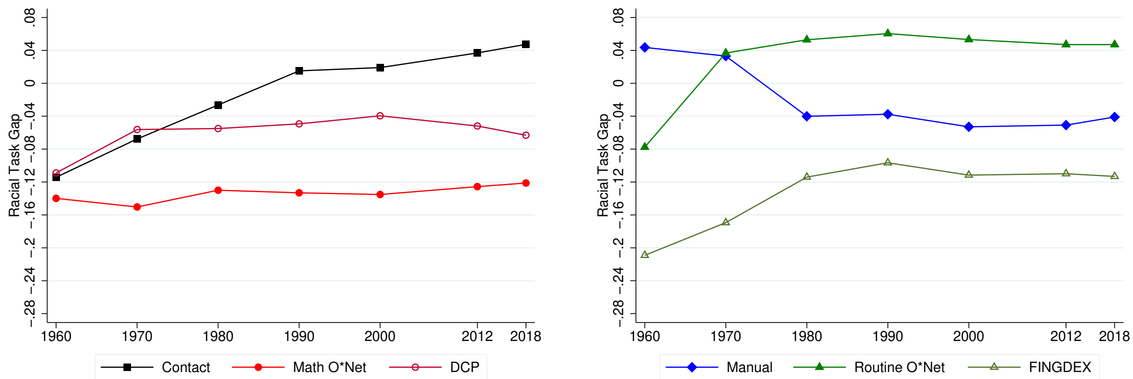
Appendix C.2 Robustness to O*Net Measures of *Math* and *Routine* Tasks

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.

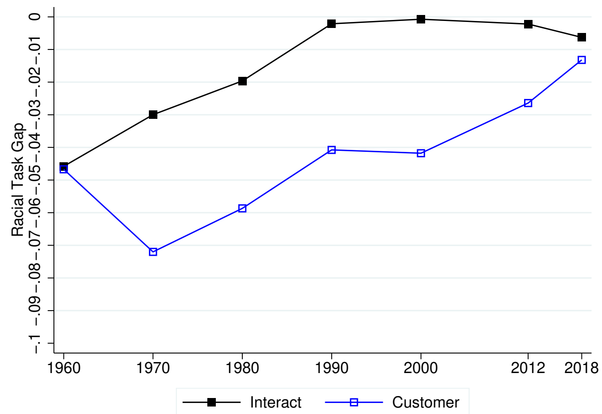
With this in mind, we explore the sensitivity of our results to using Deming's *Math* and *Routine* measure using the O*Net data as alternative task measures for the *GED-Math* and *STS* measures using the DOT data. We re-estimate the patterns in Appendix Figure R6 with the six task measures but we use 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.

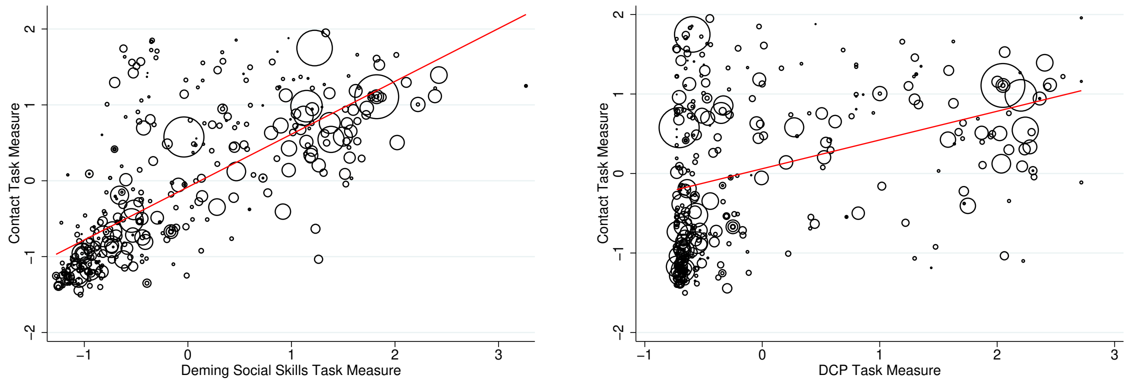
First, Appendix Figure R8 shows our key results from Figure 1 of the main text but disaggregating *Contact* into its two sub-components: *Interact* and *Customer*. The former measures the extent to which the job requires social interactions with others while the latter measures whether the job requires 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



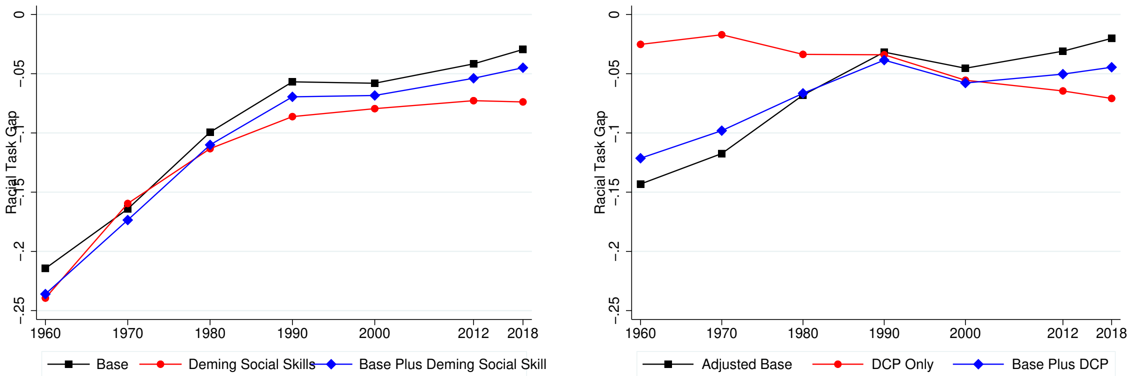
Panel A　　　　　　　　Panel B

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.

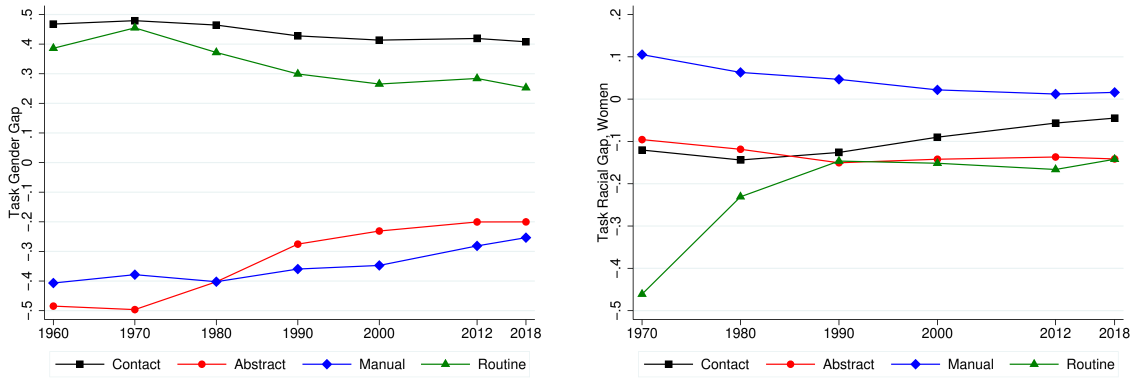
As seen from Panel A, White women are much more likely to be in *Contact* and *Routine* tasks and are much less likely to be in *Manual* and *Abstract* tasks relative to White men. Unlike the gaps between Black and White men, the gaps between White men and White women were fairly stable over the last 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 (η_{kt}^b) versus pecuniary discrimination (δ_{kt}^b) 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 ($\eta_{kt}^b + \delta_{kt}^b$). 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 (η_{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:

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

where the dependent variable $\overline{\phi}_{kt}^{wo}$ is the occupational-average of task-specific skills for task k in period t, ϕ_{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 (ϕ_{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 η^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 (δ^b_{kt}'s) after accounting for racial skill differences (η^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
η	-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
γ	-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 γ_{kt}. By bringing in data from the NLSY and using our procedure to merge in the NLSY data into our model, we find that η^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 η^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 χ_{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 η_{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.

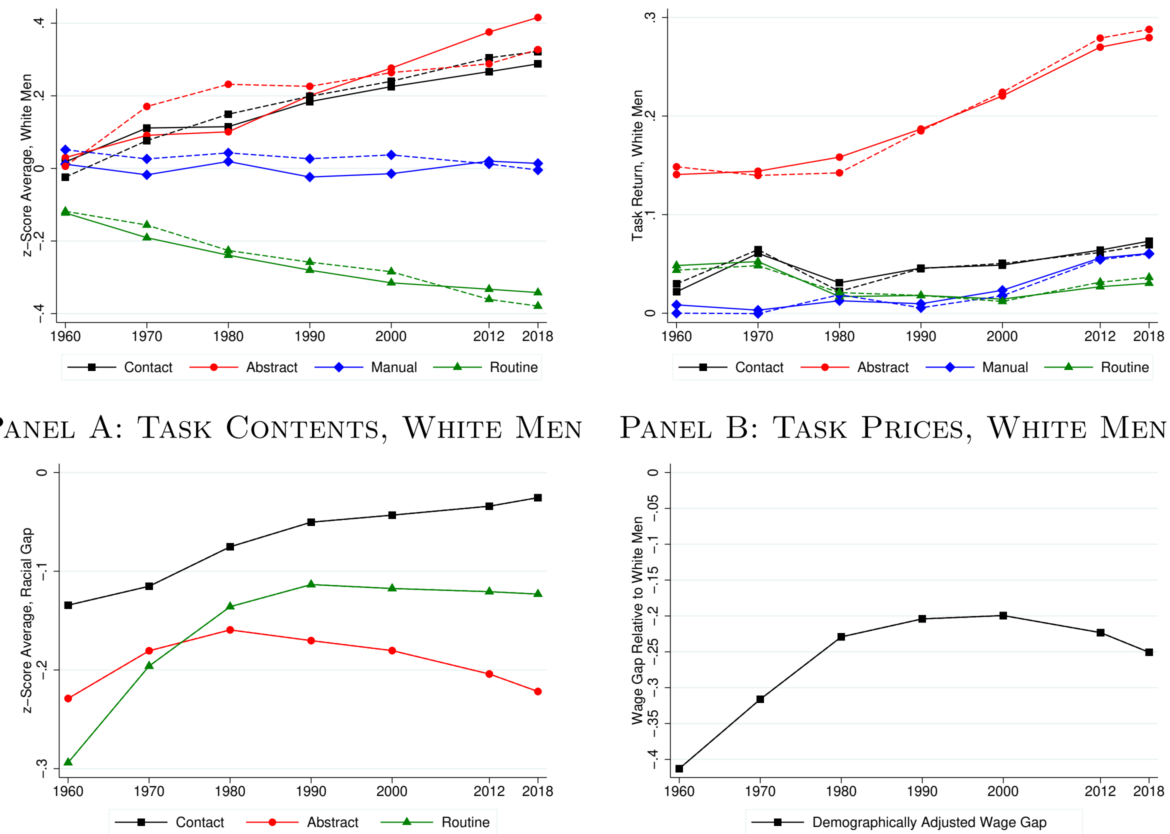
our assumption that racial barriers in *Manual* tasks are zero (which we impose because the estimated β_{kt} for *Manual* tasks is equal to or very near zero in all years) has little impact on our key paper results.

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



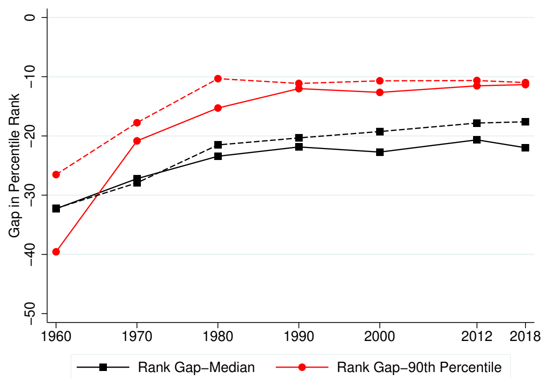
Panel C: Task Contents, Gap Panel D: Aggregate Wage Gap

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.

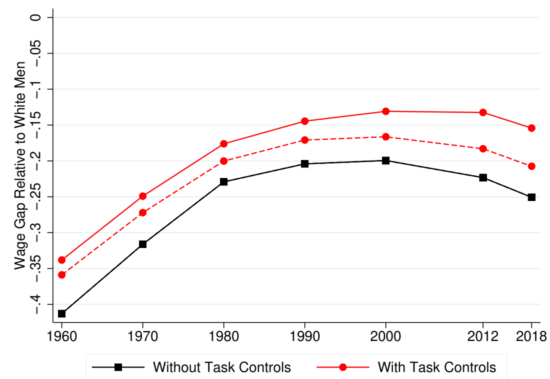
median. Likewise, a relative rank gap of -30 for the 90th percentile series implies that the 90th percentile in the Black man wage distribution is at the 60th percentile of the White man wage distribution. For this analysis, we follow Bayer and Charles (2018) and include both working and non-working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



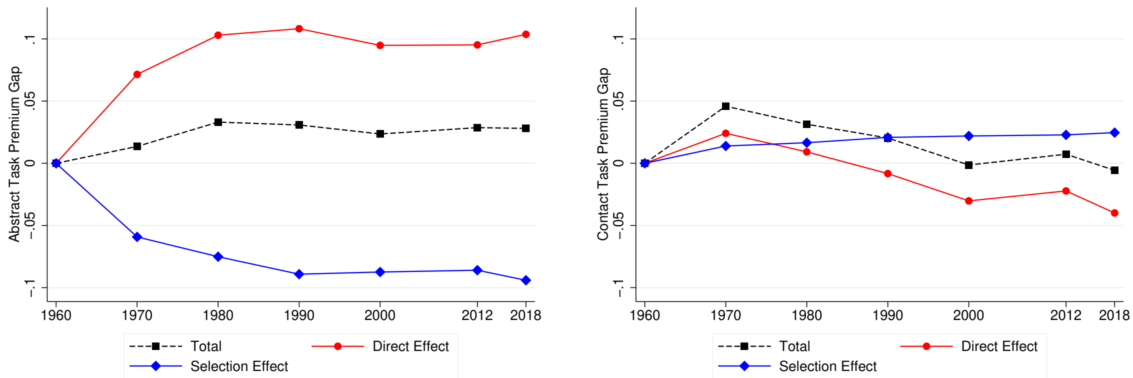
Panel B: Racial Wage Gaps Conditional on Tasks

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 τ_{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 β_{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 ψ and θ.

Appendix F.4 Robustness to Alternate ψ's

Next, we explore the robustness of our key results to alternative values of the Frechet shape parameter ψ for idiosyncratic occupational preferences. Recall from Section 4 that we externally set the value of ψ 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 ε^g_t and the employment rate L^g_t under reasonable values of ψ and θ:

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

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 β_{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 ψ. 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 ψ'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 (γ_{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 ψ 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 ψ.

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 ψ 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 ψ 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 β'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 ψ matters. This also explains why our model estimates are roughly similar to the results implied by the model-guided empirical exercises in Section 6.

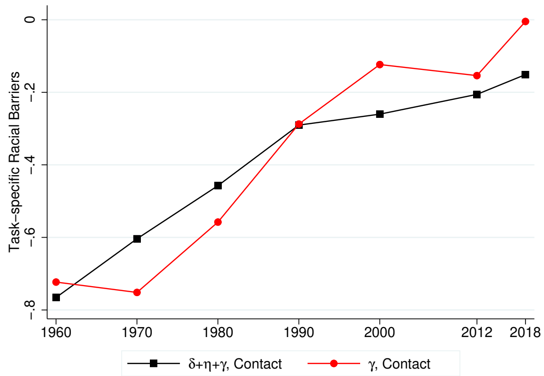
Overall, we conclude that both of our two key contributions are robust to alternative values of ψ's within a reasonable range.

Appendix F.5 Robustness to Alternate θ's

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

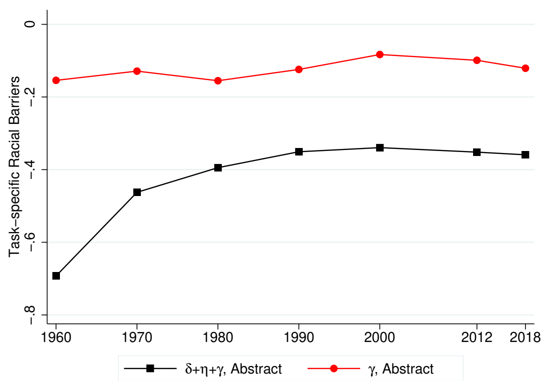
[A15]This is closer to the upper bound of the reasonable range suggested by Chetty et al. (2013). We make this choice because ε_t^g in our model maps to the elasticity over 10 years.

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

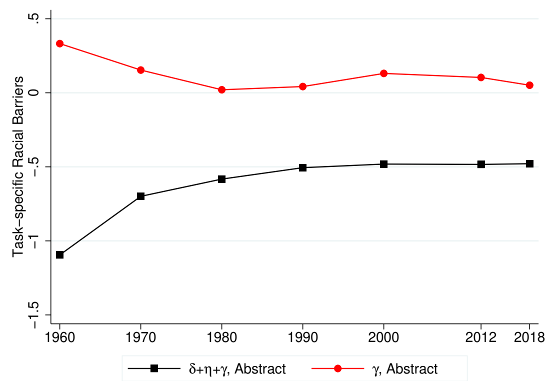


Panel A: $\psi = 3.5$, Contact

Panel B: $\psi = 5.5$, Contact



Panel C: $\psi = 3.5$, Abstract



Panel D: $\psi = 5.5$, Abstract

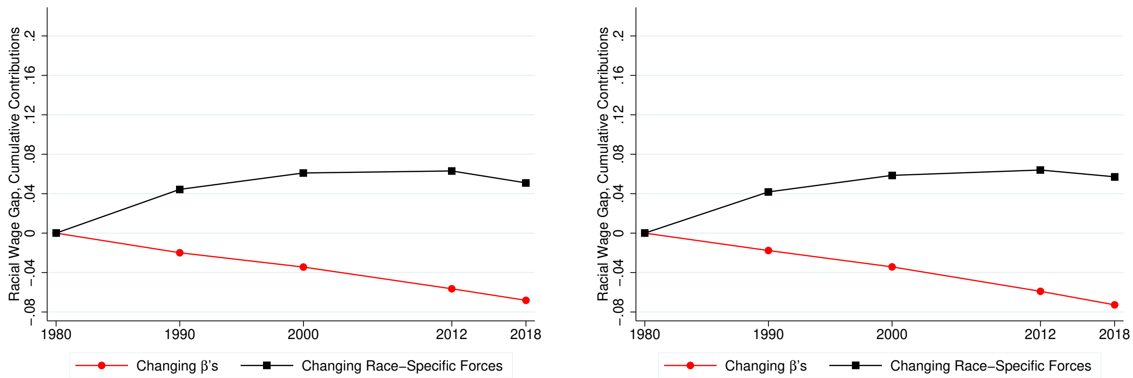
Notes: Figure shows our model estimates of the composite racial barrier ($\eta^b_{kt} + \delta^b_{kt} + \gamma^b_{kt}$) and the component that is due to non-pecuniary discrimination (γ^b_{kt}) for *Contact* tasks (Panels A and B) and *Abstract* tasks (Panels C and D). Panels A and C show estimates under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

distributions. In the baseline specification, we choose θ 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 θ. Indeed, the sensitivity analysis in Appendix I.4 reveals that small changes in the moments can shift the estimate of θ. 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 ∞ as $\theta \to 2$. Thus, we consider the values of θ 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 θ the tail of the distribution becomes sufficiently thin that raising θ further matters less at the margin.

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



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

Notes: Figure shows cumulative contributions of race-neutral forces (β_{kt}'s) and race-specific forces (δ^b_{kt}'s, η^b_{kt}'s, γ^b_{kt}'s, and A^b_t's) to the evolution of the racial wage gaps over the 1980 to 2018 period when ψ is set to 3.5 (Panel A) and 5.5 (Panel B).

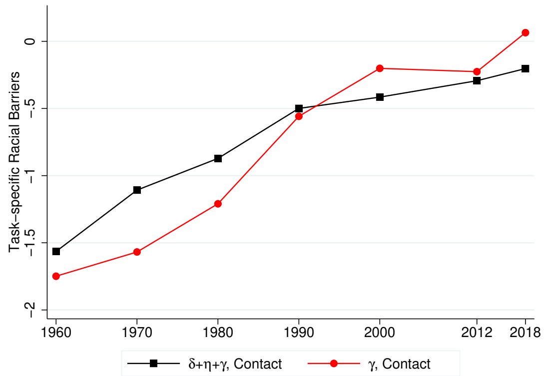
provide a good proxy for direct discrimination. Figure R17 plots the model estimates of the composite racial barrier ($\eta^b_{kt} + \delta^b_{kt} + \gamma^b_{kt}$) and the component that is due to non-pecuniary discrimination (γ^b_{kt}) for *Contact* tasks (Panels A and B) and *Abstract* tasks (Panels C and D) under the alternative values of θ. 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 θ 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 θ.[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 θ 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 θ.

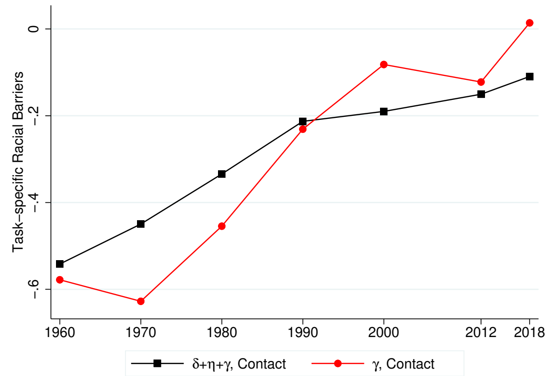
[A17]However, the size of the estimated task-specific racial barriers is much smaller with the higher value of θ. This is largely because a higher θ (i.e. thinner tail of the skill distribution) implies a higher β_{kt}'s – both because the mean of the skill distribution falls with θ and because the thinner 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 β_{kt} for *Abstract* being larger when $\theta = 2.8$.

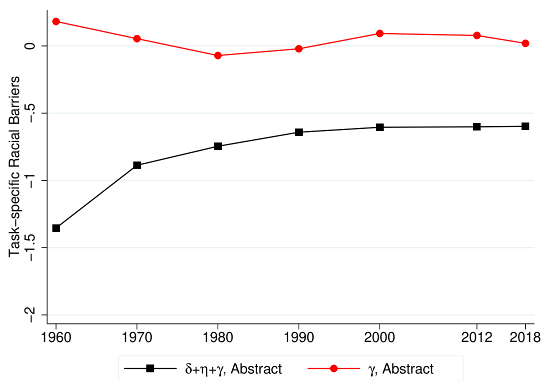
Figure R17: Task-Specific Racial Barriers for *Abstract* and *Contact* Tasks, Alternate θ's



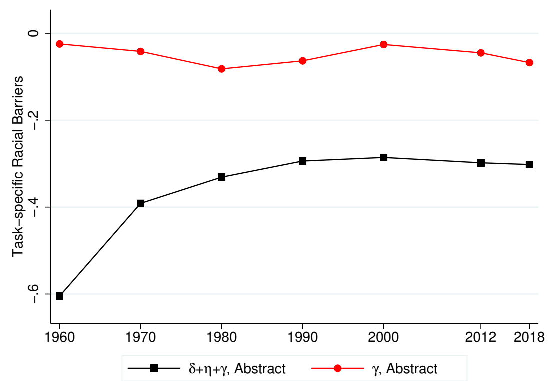
PANEL A: $\theta = 2.8$, CONTACT



PANEL B: $\theta = 4.5$, CONTACT



PANEL C: $\theta = 2.8$, ABSTRACT



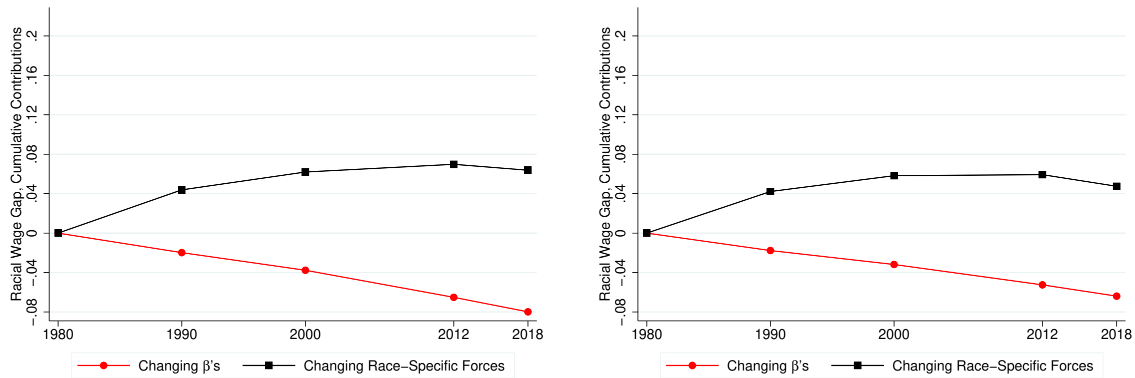
PANEL D: $\theta = 4.5$, ABSTRACT

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 (γ^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, η^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 θ's



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

Notes: Figure shows cumulative contributions of race-neutral forces (β_{kt}'s) and race-specific forces (δ^b_{kt}'s, η^b_{kt}'s, γ^b_{kt}'s, and A^b_t's) to the evolution of the racial wage gaps over the 1980 to 2018 period when θ 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 ϵ_{ik} is drawn from a normal distribution with mean zero and variance σ^2 (common to all groups). Employers, however, observe worker's group affiliation and know the underlying distributions of $\eta^g_k + \phi_{ik}$ and ϵ_{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 δ^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 η_k^g is non-zero and σ^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 π_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 η_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 (σ^2). If the signal is perfect (σ^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 δ_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 δ_{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 σ^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 δ_{kt}^b.[A20] Thus, even if we do not model statistical discrimination explicitly, the pecuniary discrimination term δ_{kt}^b will capture the effects of statistical discrimination when we estimate the model. Unless we want to assess how much of δ_{kt}^b is due to statistical discrimination – which is in any case not possible without an assumption on the amount of noise σ^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 (η_{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 δ_{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 δ_{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 σ^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 γ^g_{ot}, and their non-pecuniary idiosyncratic preference for occupations $\log \nu_{io}$. Recall furthermore that the occupational preferences ν_{io} follow a Frechet distribution with scale 1 and shape ψ. 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_ν and F_ν 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 ψ 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, τ_{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 ε_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 ψ times the home sector share. We use this fact to set the value of ψ.

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 τ_{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 β_{kt}'s scale the task requirements accordingly.

In fact, while we assume τ_{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 β_{kt}'s scale τ_{kt}'s, a uniform proportional increase within all occupations in the requirement for one task is isomorphic to an increase in the β_{kt} for the task. Thus, any systemic change to the task structure of the economy will be captured in the model as changes in β_{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 τ_{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 Θ_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 Θ^w. Let G_w^w denote the Jacobian of the moment function for Whites, $m^w(\Theta^w)$, at the true parameter set Θ_0^w. The *sensitivity* matrix Λ^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 Λ^w is a local approximation to the mapping from moments to estimated parameters. Specifically, the ij-th entry of Λ^w shows how much the estimate of the i-th parameter in Θ^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 Θ^w and Θ_t^b, respectively, again evaluated at the true parameter values Θ_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 Λ^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 Θ^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 β_{kt} for each task in each period, A_o for each occupation, and the time-invariant shape parameter θ 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 β_{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 β_{kt} in the year relative to β_{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 β_{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 β_{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 θ 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 θ at its estimated value. In general, changes in θ naturally induce re-scaling of the β'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 θ fixed makes the sensitivity matrix easier to interpret, as it keeps the scaling of parameters the same. We will later discuss the sensitivity of θ to the moments.

Tables R7 and R8 show selected entries from the sensitivity matrix Λ^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 β_{kt} and A_o – defined below – for ease of interpretation. First, we define $\bar{\beta}_k$ to be the average of β_{kt} across all periods t and look at the deviation of the β_{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 τ_{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 τ_{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 θ 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 β_{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 β_{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 β_{kt} is especially strong for workers with high task-specific skill ϕ_{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 θ fixed. Next, we consider the sensitivity of the estimated θ 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 θ. As we saw above, for a given θ, raising β_{kt} naturally increases both aggregate task content and Mincerian task premium in the task. But, holding θ fixed, it is generally not possible to fit *both* moments simultaneously just by varying β_{kt}'s. Nonetheless, we claimed, we may hope to fit both moments more closely by varying θ, as this parameter controls the relative responsiveness of task premiums and task contents to β_{kt}. In this last analysis, we shall substantiate this claim.

Table R9 presents the sensitivity of the estimated θ 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 ϕ_{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 θ is most responsive to *Abstract* task contents as well as *Contact* and *Abstract* task premiums. However, the direction of the change in θ differs by year. For example, an increase in *Abstract* task premium in 2000, 2012 and 2018 lowers θ, while a rise in the task premium in earlier years increases θ, 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 θ controls the thickness of the tail of the skill distribution. In particular, a lower θ makes the tail of the skill distribution thicker and hence makes the task premiums more responsive to a rise in β_{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 θ (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 θ (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 θ, while a rise in the task premium in earlier years reduces θ, 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 θ 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 θ fixed, while the estimated θ is far more sensitive to the moments. As noted above, changing θ in turn will require rescaling of all parameters. Because of this, our sensitivity analysis is less informative when θ 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 θ, too. In Appendix F.4, we explore the robustness of our main results to alternative values of θ.

[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 θ.

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

		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 θ 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 θ

		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 θ 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 θ 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
θ	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
θ	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 θ 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 $\delta^b_{kt} + \eta^b_{kt} + \gamma^b_{kt}$ and the racial gap in home sector returns A^b_{Ht} 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., $\delta^b_{kt} + \eta^b_{kt}$ versus γ^b_{kt} — based on the observed racial gaps in Mincerian task premiums, noting that non-pecuniary discrimination γ^b_{kt} 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^b_t. 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 $\delta^b_{kt} + \eta^b_{kt} + \gamma^b_{kt}$ and A^b_{Ht}; likewise, the aggregate racial wage gap has no impact on our estimates of γ^b_{kt}'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 $\delta^b_{kt} + \eta^b_{kt} + \gamma^b_{kt}$ 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 γ^b_{kt} more negative). Finally, a smaller racial wage gap maps one-to-one to a less negative A^b_t, 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}, β_{kt}'s, $\delta_{kt} + \eta_{kt}$'s, γ_{kt}'s, A^b_t, and A^b_{Ht} — 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 $\vec{x}_t = (A_{Ht}\ \{\beta_{kt}\}_k,\ \{\delta_{kt} + \eta_{kt}\}_k,\ \{\gamma_{kt}\}_k,\ A^b_t, A^b_{Ht})$ 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 $\overline{\omega}^{gap}(\vec{x}(s)) \equiv \overline{\omega}^{agg}_b(\vec{x}(s)) - \overline{\omega}^{agg}_w(\vec{x}(s))$ 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, τ_{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^b_H	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
γ, Contact	-0.89	-0.08	9.54	2.89	-9.99	0.00	0.00
γ, 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^b_H	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
γ, Contact	-0.91	-0.04	7.90	1.90	-8.30	0.00	0.00
γ, 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^b_H	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
γ, Contact	-0.67	-0.06	9.70	2.30	-9.73	-0.00	0.00
γ, 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^b_H	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
γ, Contact	-0.33	-0.06	9.03	1.99	-9.00	-0.00	0.00
γ, 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^b_H	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
γ, Contact	-0.12	-0.12	9.13	1.99	-8.92	0.00	0.00
γ, 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^b_H	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
γ, Contact	-0.16	-0.15	8.82	1.96	-8.39	0.00	0.00
γ, 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^b_H	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
γ, Contact	0.02	-0.09	8.50	1.87	-8.05	-0.00	0.00
γ, 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.