Task-Based Discrimination*

Erik Hurst Yona Rubinstein Kazuatsu Shimizu

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Abstract

We introduce a concept of task-based discrimination to identify and quantify the impact of labor market discrimination, skills and task returns on the Black-White gaps in occupational sorting and wages over the past half century. At the heart of our framework is the idea that discrimination varies by the task requirement of each job. We develop a Roy model where task-specific racial barriers induce racial differences in occupational sorting along task dimensions. Then, using Census, ACS and NLSY data, we document racial differences in occupational sorting along task dimensions and infer trends in the underlying task-specific racial barriers through the lens of the model. In the early 1960s, Black workers faced high barriers to entry into occupations requiring either complex analytical activities – *Abstract* tasks – or interactions with customers and co-workers – *Contact* tasks. Since then, the barriers deterring entry of Black men into occupations requiring *Contact* tasks diminished sharply, while substantial racial barriers remained in occupations requiring *Abstract* tasks. Our structurally estimated model and reduced-form estimates indicate that, during the last forty years, the increasing returns to *Abstract* tasks since the early 1980s — which on average favored White workers relative to Black workers — masked the reduction in the Black-White wage gap coming from the narrowing of racial skill gaps and the decline in labor market discrimination over the same period. Additionally, we show a variety of evidence highlighting that the racial gap in *Contact* tasks is a good proxy for taste-based discrimination.

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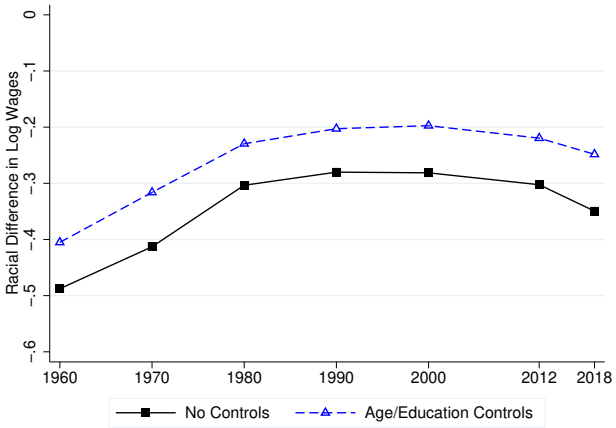
1 Introduction

Figure 1 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 and without controlling for years of schooling. The unconditional Black-White wage gap narrowed substantially from about 50 log points in the early 1960s to about 30 log points by 1980. Some researchers have attributed the rapid growth in Black relative wages during this period to declining discrimination stemming from the passage of civil rights legislation (Freeman (1973), Donohue and Heckman (1991)) while others have pointed to relative improvements in Blacks' school quality and market skills (Smith and Welch (1989), Card and Krueger (1992)).

Figure 1: Trends in Black-White Wage Gaps Since 1960, Census/ACS Data



Notes: Figure shows the trend in the Black-White gap in log wages between 1960 and 2018. The 1960 to 2000 data come from the US Censuses while the 2012 and 2018 data come from the American Community Surveys. Sample restricted to Black and White native born employed men between the ages of 25 and 54. The dashed line reports the mean racial gap in log wages conditional on five year age dummies and years of schooling. Wages are defined as annual earnings divided by annual hours worked. See the data discussion later in the paper for additional details on sample and variable construction.

However, since 1980, the Black-White wage gap has remained essentially constant. The relative stagnation in labor market progress of Black men during the last forty years has been seen as a puzzle given the documented declines since 1980 in White's reported discriminatory attitudes (Krysan and Moberg (2016), Lang and Lehmann (2012)) and a continued racial convergence in characteristics and skills that are rewarded in the labor market (Altonji et al. (2012), Bayer and Charles (2018), Dickens and Flynn (2006), Murray (2007)). In their recent review article on racial discrimination in the labor market, Lang and Lehmann (2012) point to this puzzle and conclude that "existing models of discrimination generally cannot explain

the evolution of wage and employment disparities over time either because they predict a constant level of discrimination regardless of the extent of prejudice or because we would expect a steady decline in wage and employment disparities as discrimination declines".

In this paper, we attempt to solve the puzzle by introducing a framework that integrates notions of discrimination and racial differences in skills into a task-based model of occupational sorting. 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. For example, one might imagine that taste-based discrimination operates more in occupations that require interactions with others. Indeed, using data from the U.S. Censuses and American Community Surveys, we document that Black and White men systematically sort into occupations that have different task requirements. The differential sorting patterns along task dimensions are indicative of underlying racial barriers whose intensities vary depending on task contents of occupations, such as task-based discrimination and racial differences in task-specific skills.

Merging notions of labor market discrimination and racial skill gaps into a task-based model of occupational sorting has two implications. First, the existence of task-specific racial barriers imply that race-neutral changes in task prices can affect the evolution of the Black-White wage gap even when race-specific forces – such as discrimination and racial skill gaps – remain fixed over time. We show both through the lens of our structural model and by using detailed panel micro data on racial wage gaps from the National Longitudinal Surveys of Youths (NLSY) that the rising relative return to *Abstract* tasks post-1980 substantially widened the racial wage gap during the 1980 to 2018 period and masked the effect of narrowing racial skill gaps and declining discrimination that would have otherwise caused a sizeable convergence in the racial wage gap over the period. Second, the task-based framework also implies that, by focusing on racial differences in occupational sorting along a task dimension where there is little racial skill gap, one can infer the contribution of declining racial prejudice to the evolution of the racial wage gap over time. Our collective findings reconcile the puzzle of 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; they furthermore reveal the extent of Black progress stemming from a decline in labor market discrimination.

Our paper contributes to a large amount of recent theoretical and empirical work emphasizing 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 (Autor et al. (2003), Dorn (2009), Autor and Dorn (2013), Acemoglu and Autor (2011), Acemoglu and Restrepo (2021)). Our framework is based on a Roy model proposed by Autor and Handel (2013): individuals are endowed with task-specific skills; there are many potential tasks and, in turn, many different types of skills; occupations are combinations of tasks with different weights and individu-

als have different mixtures of skills. We generalize this race-neutral task-based framework of occupational sorting by introducing two types of *race-specific* driving forces which are allowed to evolve differentially over time: task-specific racial skill gaps and task-specific discrimination.[1] These forces capture two of the most prominent race-specific explanations for why the average wages of Black and White workers differ from each other. The existence of task-specific racial differences in pre-labor market skills and task-specific labor market discrimination gives rise to differential occupational sorting along task dimensions between Black and White individuals in the spirit of Roy (1951).[2]

The existence of race-specific barriers in our model implies that *race-neutral* driving forces may affect the evolution of racial wage gaps even when the race-specific driving forces are held fixed. To set ideas, consider a scenario where Black men either have a racial skill gap associated with some task k or face discrimination associated with performing task k. In such a world, Black men will be systematically underrepresented in occupations that require relatively more of task k. Given the existence of race-specific barriers in task k – which create a wedge in the return to performing the task between Black and White men – and given the resulting under-representation of Black men in occupations requiring task k intensively, an increase in the return to task k – relative to other tasks – will increase the average wages of White workers relative to Black workers, all else equal. In a world with task-specific racial barriers, race-neutral changes in task returns will influence the racial wage gap.

In terms of estimation, our structural model implies that one can infer the magnitudes and changes over time in race-specific barriers from racial differences in occupational sorting along task dimensions. In view of this, we document a new set of facts about racial differences in occupational sorting along task dimensions. Drawing on the existing literature, we characterize occupational sorting along four key labor demand factors: "*Abstract*", "*Routine*", "*Manual*", and "*Contact*" tasks. The first three task measures come directly from Dorn (2009) and Autor and Dorn (2013), while the last measure is new and guided by Becker (1957)'s work on taste-based discrimination. Specifically, "*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 verify ex-post that this task provides a measure of labor market activities where taste-

[1] 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 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)).

[2] 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. Given these findings, we also explicitly include in our model a margin of labor force participation that can evolve differentially over time by race.

based discrimination is likely to be the most salient because the task requires interacting with others who may have discriminatory preferences.

Using micro-data from the US Censuses and American Community Surveys (ACS), 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 has remained essentially constant through 2018. This finding holds regardless of whether or not we control for trends in racial gaps in accumulated levels of schooling. Conversely, we show that the large racial gap in the extent to which workers sort into occupations that require *Contact* tasks that existed in 1960 has narrowed substantively by 2018. Finally, we show that the racial gap in the *Routine* task content of occupations narrowed from 1960 to 1980 but then started diverging post-1980.

We then discipline our structural model using the documented racial task gaps and find that the stagnation in the racial wage gap post-1980 is a product of two offsetting forces. On the one hand, a narrowing of racial skill gaps and declining discrimination between 1980 and 2018 caused the racial wage gap to narrow by about 6.5 percentage points during this period, all else equal. 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 6.5 percentage points during the same period. Intuitively, the large rise in the return to *Abstract* tasks post-1980 disadvantaged Black workers because they were underrepresented in these tasks due to large race-specific barriers they faced in *Abstract* tasks. Black progress stemming from narrowing racial skill gaps and/or declining discrimination did not translate into Black-White wage convergence during the 1980-2018 period because the rising returns to *Abstract* tasks masked the progress. As a point of comparison, we show that the relative wage gains of Black men during the 1960-1980 period stemmed solely from improving race specific factors, consistent with the literature highlighting the importance of the Civil Rights Act in reducing racial wage gaps during this period. Given that the labor market returns to the various task measures trended similarly between 1960 and 1980, changing task prices did not undermine any of the race-specific gains during this earlier period.

Our structural model provides a road map to empirical researchers 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. Using data from the National Longitudinal Survey of Youth (NLSY), we implement our model suggested reduced-form regressions. We find that controlling for time-varying returns to tasks does, in fact, uncover a strong convergence in racial wage gaps during the last four decades in the United States. The magnitude of the convergence in the racial wage gap is similar to the effect of declining race specific factors predicted by our structural model. With this discussion

we also highlight why our task-based model yields quantitatively different conclusions about the extent to which race-specific forces have changed in the U.S. economy during the last forty years relative to methodologies that rely on purely statistical decomposition procedures (e.g., Juhn et al. (1991)) and ignore task-based sorting forces.

In the last part of the paper, we go one step further and show that the racial gap in *Contact* tasks is indeed a good proxy for taste-based discrimination. Again, bringing in additional data from the 1979 and 1997 NLSY's, we show how various measures of individual's pre-labor market traits predict the task composition of their occupations when adults. In particular, individuals in the NLSY with high measures of "cognitive" skills when young (as measured by scores on the Armed Forces Qualifying Test (AFQT)) are much more likely to sort into occupations that require *Abstract* tasks during their working years. Conversely, individuals with high "social" skills (based on survey questions designed to measure personality traits like extroversion) are much more likely to sort into occupations that require *Contact* tasks. Within the NLSY data, we find no racial differences in the extent of social skills in any time period. However, consistent with Neal (2006) and Altonji et al. (2012), we find large but narrowing racial differences in the extent of cognitive skills.

Using the above NLSY data as inputs, we then develop a procedure which translates racial gaps in NLSY pre-labor market traits into racial gaps in model-generated task-specific skill gaps. The procedure consists of two steps. First, we load our model-generated average task-specific skills by occupation onto the NLSY measures of average cognitive, non-cognitive, and social pre-labor market skills by occupation, as measured among White workers. Second, we use these loadings and the racial gap in various NLSY pre-labor market traits to create a model-based estimate of racial skill gaps associated with each task in each period consistent with the racial gaps in pre-labor market traits found in the NLSY. Based on this procedure, our model estimates that the racial gap in *Contact* tasks is driven almost entirely by discrimination. This result stems from the fact that (i) there are almost no racial gaps in social skills and (ii) of all of our pre-labor market trait measures from the NLSY, social skills are the most predictive of entry into occupations that primarily require *Contact* tasks. These empirical findings viewed through the lens of the model imply that the racial barriers we estimate for *Contact* tasks is mainly attributed to taste-based discrimination.

This finding confirms our ex-ante conjecture that the evolution of the racial gap in *Contact* tasks is a good predictor of the change in taste-based discrimination. To further provide evidence for this conclusion, we use data from Charles and Guryan (2008), which provide survey-based measures of taste-based discrimination for each U.S. state. Using cross-state variation, we show that racial gaps in *Contact* tasks are strongly correlated with the Charles-Guryan state-level measures of taste-based discrimination. We find a much weaker correlation

with state-level measures of racial gaps in *Abstract* tasks. We conclude the paper by using the estimated model to quantify how much the changes in each of the driving forces over time contributed to the evolution of the racial wage gap over the last half century. We estimate that at least 60 percent of the decline in the overall racial wage gap between 1960 and 2018 can be attributed to declining taste-based discrimination. This estimate is almost certainly a lower bound given that any remaining racial skill gaps which drive a wedge between the wages of Black and White men are almost certainly the result of current and past discrimination.

Related Literature Our paper contributes to the growing literature highlighting the importance of task based models of occupational sorting for understanding changes in inequality within the U.S. labor market since 1980 (Autor et al. (2003), Dorn (2009), Autor and Dorn (2013), Deming (2017), Acemoglu and Restrepo (2018), Acemoglu and Restrepo (2021)).[3] Recently, Acemoglu and Restrepo (2021) developed and estimated a task-based model to document how automation has contributed to the relative wage declines of workers specializing in tasks associated with industries experiencing rapid automation during the past four decades. We contribute to this literature by using a task model to explain changing racial inequality across groups over time. By embedding racial differences into a task model of occupational sorting, we explore the extent to which changes in task returns can help to reconcile the puzzle as to why the Black-White wage gap stagnated since 1980. Additionally, we show how different tasks can be informative about the extent of taste-based discrimination within the economy.[4]

Contemporaneously, Kline et al. (2021) use a large scale randomized experiment sending out fictitious job applications to large employers to shed light on current taste-based discrimination in hiring within the United States. They find that some firms are still unwilling to interview applications with Black sounding names relative to otherwise similar White workers. Consistent with our findings, they find that the racial gap in call back rates was highest in occupations that require workers to interact with customers. The findings in Kline et al. (2021) provide additional supportive evidence for one of our main findings through the lens of our structural model and our cross-region evidence that the racial gap in *Contact* tasks is a good proxy for taste-based discrimination.

Our paper is also related to papers such as Juhn et al. (1991) and Bayer and Charles's

[3]For a recent discussion of this literature, see Acemoglu and Autor (2011).

[4]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 gender who face differential frictions in both human capital and labor markets. The goal of Hsieh et al. (2019) is to provide a framework with economically meaningful sorting to assess the role of changes in racial and gender barriers during the last half century to economic growth. There is also a small literature documenting the evolution of gender differences in the task content of occupations. See, for example, Black and Spitz-Oener (2010) and Cavounidis et al. (2021).

(2018) that estimate how changes in aggregate skill returns can affect the Black-White wage gap.[5] For example, Bayer and Charles (2018) importantly attribute the lack of positional improvement for median Black men since 1940 despite the narrowing of the racial education gaps to differential trends in the returns to high school versus post-secondary schooling. The rising return of college education relative to high school education disadvantaged Black men as they still disproportionately possess lower levels of school credentials. We use their result as a launching point for our approach and study the trends in Black-White gaps *conditional on schooling*. In particular, focusing on the fact that Black-White labor market progress has stalled even conditional on education, we extend their insights to a task-based model of occupational sorting with multiple tasks and show that higher returns to *Abstract* tasks have disadvantaged Black men relative to White men even conditional on education.

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. Our model builds upon Autor and Handel (2013), which propose a Roy model where workers with differential skill endowments self-select into occupations according to their task requirements. We extend their framework by introducing two *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.

The framework allows us to structurally estimate the time-trends of race-specific and race-neutral driving forces, and to quantify the importance of the respective force in explaining changes in the racial wage gap (or lack of thereof) over time. The framework also suggests a reduced-form empirical methodology for uncovering changes in race-specific driving forces using panel micro data on the wages and occupational choices. This section derives theoretical results that will guide our quantitative and empirical exercises throughout the paper.

[5] There is an extensive literature exploring racial differences in labor market outcomes. Smith and Welch (1989), Altonji and Blank (1999), Lang and Lehmann (2012), and Lang and Kahn-Lang Spitzer (2020) provide excellent surveys of this literature. Surveying this literature is beyond the scope of our paper.

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, i.e., a relatively high τ_{ok} for task k; relatively high amounts of multiple (or even all) tasks; or relatively low amounts of all tasks. We use microdata on the task requirements of different occupations to discipline the τ_{ok}'s.

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 potential 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 "taste-based" discrimination in a particular task in the spirit of Becker (1957); conditional on their task-specific skills, we allow workers to be paid less than their marginal product. Finally, groups are allowed to differ in their relative utility in the home sector. This feature allows for the possibility of differential employment rates across groups conditional on other model driving forces. All three 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 each worker draws differential efficiencies at performing each type of tasks from a known distribution. Omitting time subscripts, we denote the skill-endowment of worker i belonging to group g with a vector $\overrightarrow{\phi_{gik}} = \{\phi_{gi1}, ..., \phi_{giK}\} \in \mathcal{R}_+^K$, where ϕ_{gik} 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 $\overrightarrow{\phi_{wik}} = \{\phi_{i1}, ..., \phi_{iK}\}$, 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.[6] For Black men (g=b), we assume the vector of skill draws can be expressed as $\overrightarrow{\phi_{bik}} = \{\eta_{b1}+\phi_{i1}, ..., \eta_{bK}+\phi_{iK}\}$, where η_{bk} measures the relative gap in average

[6]The normalization of the scale parameter to 1 of the skill draws for White men is innocuous given we allow the returns to skills to scale freely when calibrating the model. The implicit normalization of the location parameter to zero is also innocuous since it will be absorbed by occupation effects defined below; however, in general, the model can allow negative skill endowments.

task-specific skills between Black and White men. In short, the skill distribution for Black men is shifted by η_{bk} 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_{bk}'s proxy for the 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_{bk}'s to differ by task and to evolve differentially over time. Adding this force to the model allows changes in both the racial wage gap and racial gaps in occupational sorting to be driven, in part, by a narrowing of task-specific racial skill gaps over time.

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 race groups and constant over time. The idiosyncratic preference draws are needed to match the distribution of occupational sorting observed in the data within each group g.

Collectively, individual i is defined by $\overrightarrow{\phi_{gik}}$ (their vector of K task-specific productivity draws), $\overrightarrow{\nu_{io}}$ (their vector of O occupation-specific preference draws), and g (the group to which they belong).

2.3 Worker Wages

Given the existence of racial skill gaps and taste-based discrimination, the labor market wages and occupational choice of Black and White workers will differ from each other on average. Define the potential log wage ω that worker i belonging to race group White men (g=w) would earn in occupation o in period t as:

$$\omega_{wiot} = A_{ot} + \sum_{K} \beta_{kt} \tau_{ok} \phi_{ik}, \tag{1}$$

where A_{ot} is an occupation-specific constant representing the potential log wage that a worker with no skills would earn in occupation o during period t. Variation in A_{ot} over time proxies for changes in occupational demands or occupational productivities which cause some occupations to grow in employment relative to other occupations with the same task bundle. $\beta_{kt} \geq 0$ is the return to each task, which is also allowed to vary over time. Allowing β_{kt} to vary over time allows us to explore how changing returns to different tasks can influence occupational sorting and the racial wage gap. Note, in our base model, we assume the task content of the occupations τ_{ok} are time invariant; we explore the sensitivity of our results to

this assumption in our empirical work.

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

$$\omega_{biot} = A_{ot} + \sum_{K} \beta_{kt}\tau_{ok} \left((\delta_{bkt}^{taste} + \eta_{bkt}) + \phi_{ik} \right), \tag{2}$$

where A_{ot}, β_{kt}, and τ_{ok} are as defined above. Conditional on choosing occupation o and drawing a set of task-specific skills (the ϕ_{ik}'s), Black workers may earn different wages than White workers for two reasons. First, there could be differences in average task-specific skills between the groups (the η_{bkt}'s). Second, there could be task-specific discrimination affecting Black workers (the δ_{bkt}^{taste}'s). This is a proxy for anything that causes differences in wages conditional on skills.[7] The composite race-specific barrier $\delta_{bkt}^{taste} + \eta_{bkt}$ causes the marginal return to sorting into occupations with high task-k requirements to systematically differ between Black and White workers, and thus induces differential sorting patterns by race.

2.4 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. This could be important when measuring racial wage gaps given differential trends over time in labor supply for Black and White men. Specifically, we treat the home sector as another potential occupation with task requirements $\tau_{H1}, ..., \tau_{HK}$ and (non-pecuniary) occupational return A_{gHt}. Hence, the reservation utility u_{giH} of a worker with given observable credentials equals the log of the worker's expected marginal revenue product in the home occupation given home sector task requirements ($\tau_{H1}, ..., \tau_{HK}$) plus the log of the idiosyncratic preference for home sector, ν_{iH}.[8] Unlike with other A_{ot}'s, we allow the occupational return to home sector, A_{gHt}, to differ by group g. The differences in A_{gHt}'s across groups thus capture any forces other than differential task returns that may create labor supply differences between racial groups.

[7] Throughout, we will assume employers can observe a worker's skills without error. In the NBER working paper version of this paper (Hurst et al. (2021)), 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, allowing for statistical discrimination was not necessary. For parsimony, we removed our discussion of statistical discrimination from the main text and refer readers to the NBER working paper for the full model and estimation with statistical discrimination.

[8] Like the other occupational preferences ν_{io}, the preference for home sector ν_{iH} follows a Frechet distribution with shape ψ and scale 1. The normalization of the scale to one is without loss of generality.

2.5 Occupational Choice

Conditional on working, each worker sorts into the occupation o that maximizes their utility u_{giot}, which is the sum of log earnings and their non-pecuniary idiosyncratic preference for occupations $\log \nu_{io}$. Normalizing δ_{gkt}^{taste}=0 and η_{gkt}=0 for White men we get the following expression for individual utility in a given occupation o during period t:

$$u_{giot} \equiv \omega_{giot} + \log \nu_{io} = A_{ot} + \sum_{K} \beta_{kt}\tau_{ok} \left((\delta_{gkt}^{taste} + \eta_{gkt}) + \phi_{ik} \right) + \log \nu_{io}. \tag{3}$$

The workers compare their utility from working to their reservation utility from being in the home sector:

$$u_{giHt} \equiv A_{gHt} + \sum_{K} \beta_{kt}\tau_{Hk} \left((\delta_{gkt}^{taste} + \eta_{gkt}) + \phi_{ik} \right) + \log \nu_{iH}. \tag{4}$$

Given an individual's task productivity draws ($\overrightarrow{\phi_{gik}}$), their occupational preference draws ($\overrightarrow{\nu_{io}}$), the task composition of occupations (τ_{ok}), the occupation and task prices they face (A_{ot}'s and β_{kt}'s), and any other race-specific task frictions (δ_{bkt}), workers sort into different occupations so as to maximize their utility. The optimal occupational choice of worker i in group g is given by

$$o_{gi}^{*} = \arg\max_{o=1,\ldots,O,H} \{u_{gio}\}. \tag{5}$$

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).

The fact that idiosyncratic occupational preferences ν_{io} follow a Frechet distribution implies convenient closed-form expressions for occupational shares. As derived in the appendix, the fraction of group g workers who choose occupation o conditional on working and having skill draws $\vec{\phi} = \{\phi_1, ..., \phi_K\}$, $\rho_{got}(\vec{\phi})$, is given by:

$$\rho_{got}(\vec{\phi}) = \frac{\exp\{\psi\omega_{got}(\vec{\phi})\}}{\sum_{o' \neq H} \exp\{\psi\omega_{go't}(\vec{\phi})\}},$$

where $\omega_{got}(\vec{\phi})$ denotes the (log) wage that a worker of group g with skill draws $\vec{\phi}$ would receive in occupation o (c.f., equations (1) and (2)). Similarly, the labor market participation rate for group g workers with skill draws $\vec{\phi}$, $L_{gt}(\vec{\phi})$, is given by:

$$L_{gt}(\vec{\phi}) = 1 - \frac{\exp\{\psi\omega_{gHt}(\vec{\phi})\}}{\sum_{o'=1,\ldots,O,H} \exp\{\psi\omega_{go't}(\vec{\phi})\}},$$

where the home sector return is defined as $\omega_{gHt}(\vec{\phi}) = A_{gHt} + \sum_K \beta_{kt}\tau_{Hk}\left((\delta^{taste}_{gkt} + \eta_{gkt}) + \phi_k\right)$. The occupational shares and labor market participation rates over all group g workers can then be obtained by integrating over all $\vec{\phi}$ combinations.[9]

2.6 Comparative Statics and Model Implications

The model includes *race-neutral* driving forces that change the allocation of workers across occupations 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 and and race-specific driving forces.

2.6.1 Occupational Sorting and the Race-Neutral Driving Forces

Our model has two race-neutral driving forces: A_{ot} (the occupational returns) and β_{kt} (the task returns). Changes in the occupational and task returns affect the occupational choice and wages of both Black and White men.

Proposition 1. *Changes in occupational returns $A_{o't}$ ($o' \neq H$) and task returns β_{kt} impact occupational employment shares $\rho_{got}(\vec{\phi})$ for group g workers with skill draws $\vec{\phi}$ according to:*

$$\frac{d\rho_{got}(\vec{\phi})}{dA_{o't}} = \begin{cases} \psi\rho_{got}(\vec{\phi})(1-\rho_{got}(\vec{\phi})) \geq 0, & o = o', \\ -\psi\rho_{got}(\vec{\phi})\rho_{go't}(\vec{\phi}) \leq 0, & o \neq o', \end{cases}$$

$$\frac{d\rho_{got}(\vec{\phi})}{d\beta_{kt}} = \psi\rho_{got}(\vec{\phi})\left(\tau_{ok} - \overline{\tau}_{gkt}(\vec{\phi})\right)(\phi_k + \eta_{gkt} + \delta_{gkt}),$$

where $\overline{\tau}_{gkt}(\vec{\phi}) = \sum_{o\neq H}\rho_{got}(\vec{\phi})\tau_{ok}$ is the average task k content of the occupations that workers from group g with skill draws $\vec{\phi}$ sort into.[10]

The first equation shows that increases in occupational returns A_{ot} for a given occupation o – holding other occupational returns fixed – reallocates workers towards the occupation. The second equation shows that increases in task return β_{kt} for a given task k – holding all other task returns fixed – reallocates workers with high ϕ_k towards occupations that require relatively more of task k. To see the latter, notice that the derivative for occupation o is positive if its task requirement τ_{ok} is above the current average task content $\overline{\tau}_{gkt}(\vec{\phi})$ and

[9] The labor market participation rate over all group g workers is given by $\overline{L}_{gt} = \int L_{gt}(\vec{\phi})dF(\vec{\phi})$, where F is the cdf of their skill distribution; similarly, the occupation shares over all group g workers are given by $\overline{\rho}_{got} = \int \frac{\rho_{got}(\vec{\phi})L_{gt}(\vec{\phi})}{\overline{L}_{gt}}dF(\vec{\phi})$.

[10] All proofs for the propositions can be found in the online appendix.

$\phi_k + \eta_{gkt} + \delta_{gkt}$ is positive; high ϕ_k workers relocate to occupations with higher τ_{gk}. Likewise, low ϕ_k workers – those with negative $\phi_k + \eta_{gkt} + \delta_{gkt}$ – relocate to occupations with lower τ_{gk}. This result implies that, together with price information on wages, *within-group* occupational sorting patterns provide information about underlying race-neutral forces (given assumptions on skill and occupational preference distributions).

Model Implication 1: Given data on the occupational sorting and wages of White men (for whom η_{gkt} and δ_{gkt}^{taste} are zero), the task composition of occupations, and assumptions on the distributions from the ϕ_{ik}'s and the ν_{io}'s are drawn, we can separately infer the race neutral driving forces in our model in each period, the β_{kt}'s and the A_{ot}'s. In section 4.1 below we discuss in greater detail how we infer the β_{kt}'s and A_{ot}'s using the occupational sorting and wages of White men.

2.6.2 Occupational Sorting and Race-Specific Driving Forces

The model also includes two main race-specific barriers which cause the occupational choice and wages of Black and White men to diverge from each other. First, the η_{bkt}'s measure the extent to which Black and White men have different levels of task-specific skills on average. Second, the δ_{bkt}^{taste}'s measure the extent to which Black men face something akin to taste-based discrimination in each of the tasks. As seen from equation (2), it is the composite sum of η_{bkt} and δ_{bkt}^{taste} that acts a wedge in the task specific returns between Black and White men. The next proposition summarizes how changes in the race-specific barrier impacts the occupational sorting of Black men.

Proposition 2. *Changes in the composite race-specific barriers $\eta_{gkt}+\delta_{gkt}$ impact occupational employment shares of Black men as follows:*

$$\frac{d\rho_{bot}(\vec{\phi})}{d(\eta_{bkt} + \delta_{bkt})} = \psi\rho_{bot}(\vec{\phi})\left(\tau_{ok} - \overline{\tau}_{bkt}(\vec{\phi})\right)\beta_{kt}.$$

This proposition states that, when the race-specific barriers that Black workers face in task k increase (i.e., $\eta_{bkt}+\delta_{bkt}$ becomes more negative), shares of Black workers in occupations that require a relatively high intensity of that task will decline. Relative to White men, Black men will be underrepresented in occupations that are intensive in tasks for which task-specific racial barriers ($\eta_{bkt} + \delta_{bkt}$) are large.

The re-allocations induced by changes in race-neutral and race-specific driving forces will change the overall composition of tasks performed by Black and White workers. Proposition

3 examines how occupational sorting in terms of aggregate task contents $\overline{\tau}_{gkt}(\vec{\phi})$ changes in response to both changes in task prices (β_{kt}) and the composite racial barrier ($\eta_{gkt} + \delta_{gkt}$).

Proposition 3. *Race-neutral and race-specific forces impact the average task content $\overline{\tau}_{gkt}(\vec{\phi})$ performed by group g workers with skill draws $\vec{\phi}$ according to:*

$$\frac{d\overline{\tau}_{gkt}(\vec{\phi})}{d\beta_{kt}} = \psi \text{var}_{g,\vec{\phi}}(\tau_{ok})(\phi_k + \eta_{gkt} + \delta_{gkt}),$$

$$\frac{d\overline{\tau}_{gkt}(\vec{\phi})}{d(\eta_{gkt} + \delta_{gkt})} = \psi \text{var}_{g,\vec{\phi}}(\tau_{ok})\beta_k \geq 0,$$

where $\text{var}_{g,\vec{\phi}}(\tau_{ok}) = \sum_o \rho_{got}(\tau_{ok} - \overline{\tau}_{gkt}(\vec{\phi}))^2$ *denotes the variance of tasks performed τ_{ok} among 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 higher requirement for the task; however, the race-specific barriers $\eta_{bkt} + \delta_{bkt}$ can hinder the extent of the movement for Black workers. More explicitly, the second equation shows that the increase in the race-specific barriers for a task (a more negative $\eta_{bkt} + \delta_{bkt}$) deters Black workers from sorting into occupations with high requirement for the task. Importantly, Proposition 3 implies that differences in the aggregate task content of occupations between Black and White men is a key statistic that can help us infer the size of race-specific barriers $\eta_{bkt} + \delta_{bkt}$ from the data given estimates for task returns β_{kt} and other distributional assumptions.

Model Implication 2: Given estimates of β_{kt}'s and A_{ot}'s, we can infer the composite race specific barrier associated with each task in each period (the ($\eta_{bkt} + \delta^{taste}_{bkt}$)'s) from data on racial wage gaps and racial differences in occupational sorting along different task dimensions. In section 3, we use detailed micro data from the U.S. Censuses and American Community Surveys to measure racial differences in the task content of occupational sorting between Black and White men and how those differences have evolved over time.[11]

One of our main goals in the paper is to understand the evolution of the racial wage gap over time. Proposition 4 derive comparative statics on the mean (log) wage received by group g workers with skill draws $\vec{\phi}$, denoted with $\overline{\omega}_{gt}(\vec{\phi})$, with respect to key model driving forces.

[11]Propositions 1, 2, and 3 also show that the Frechet shape parameter ψ for the occupational preference distribution plays a crucial role in determining the extent of sorting responses. Intuitively, occupational preferences generate frictions for occupational sorting (which one can think of conceptually as proxies for any frictions that limit occupational sorting in the real world, e.g., labor market search). The parameter $1/\psi$ controls the heterogeneity of occupational preferences, and its choice has implications on sorting responses in the model, impacting both parameter estimation and quantitative exercises. In Section 4.1 and in the appendix, we discuss how estimates of the labor supply elasticity can be used to infer this parameter.

Proposition 4. *Race-neutral and race-specific forces impact the mean (log) wage* $\overline{\omega}_{gt}(\vec{\phi}) = \sum_{o \neq H} \rho_{got}(\vec{\phi})\omega_{got}(\vec{\phi})$ *earned by group* g *workers with skill draws* $\vec{\phi}$ *as follows:*

$$\frac{d\overline{\omega}_{gt}(\vec{\phi})}{d\beta_{kt}} = \left[\overline{\tau}_{gkt}(\bar{\phi}) + \psi \operatorname{cov}_{g,\bar{\phi}}(\omega_{got}(\vec{\phi}), \tau_{ok})\right](\phi_k + \eta_{gkt} + \delta_{gkt}),$$

$$\frac{d\overline{\omega}_{gt}(\vec{\phi})}{d(\eta_{gkt} + \delta_{gkt})} = \left[\overline{\tau}_{gkt}(\bar{\phi}) + \psi \operatorname{cov}_{g,\bar{\phi}}(\omega_{got}(\vec{\phi}), \tau_{ok})\right]\beta_{kt},$$

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

In both 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 task-specific barriers (a less negative $\eta_{bkt} + \delta_{bkt}$) will raise the return from performing the task for the group. 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 $\overline{\tau}_{gkt}(\bar{\phi})$ of their work. The second term, on the other hand, captures the indirect effect through 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. In general, the indirect effect of sorting is small relative to the first term under reasonable parameterizations.

The proposition allows us to analyze the effect of race-neutral and race-specific forces on the aggregate racial wage gap. Let $\overline{\omega}^{agg}_{gt}$ denote the mean (log) wage across all group g workers. Holding fixed the occupational choices and assuming full labor market participation for simplicity, we can write the effect of changing β_{kt} and $\eta_{bkt} + \delta_{bkt}$ on the aggregate racial wage gap $\overline{\omega}^{agg}_{bt} - \overline{\omega}^{agg}_{wt}$ roughly as:[12]

$$\begin{aligned} d(\overline{\omega}^{agg}_{bt} - \overline{\omega}^{agg}_{wt}) \approx & \sum_k \left\{ \int \overline{\tau}_{bkt}(\bar{\phi})\beta_{kt}\, dF_w(\bar{\phi}) \right\} d(\eta_{bkt} + \delta_{bkt}) \\ & + \sum_k \left\{ \int \left[\overline{\tau}_{bkt}(\bar{\phi})\,(\eta_{bkt} + \delta_{bkt}) + \left(\overline{\tau}_{bkt}(\bar{\phi}) - \overline{\tau}_{wkt}(\bar{\phi})\right)\phi_k\right] dF(\bar{\phi}) \right\} d\beta_{kt} \end{aligned}$$

There are two take-aways from this expression. First, reduction in race-specific barriers

[12] The appendix contains expressions that reflect both intensive and extensive margin adjustments in sorting in response to changing task prices and racial barriers.

$(d(\eta_{bkt} + \delta_{bkt}) > 0)$ 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 $(\eta_{bkt} < 0)$, or if they are not properly compensated for their skills due to taste-based discrimination $(\delta_{bkt} < 0)$. The second term shows that differential sorting further amplifies this effect; if skilled Black workers on average perform less of the task than comparable Whites due to high barriers – that is, if $\overline{\tau}_{bkt}(\bar{\phi}) - \overline{\tau}_{wkt}(\bar{\phi}) < 0$ – then they capture even less of the gains from rising task returns.

Model Implication 3: Given the existence of given task-specific racial barriers $(\eta_{bkt} + \delta^{taste}_{bkt})$, changes in race-neutral task returns (β_{kt}'s) will cause changes in the racial wage gap. Hence, we cannot infer changes in the composite race specific forces $(\eta_{bkt} + \delta^{taste}_{bkt})$ without controlling for changing task-specific returns over time. Below, we will highlight this implication both through the lens of our estimated model and through reduced-form estimation using micro-level panel data.

2.6.3 Separating the Race-Specific Driving Forces From Each Other

The above discussion highlights that one cannot separate the composite race-specific forces $\eta_{bkt} + \delta_{bkt}$ into taste-based discrimination (δ_{bkt}) and racial skill differentials (η_{bkt}) just from information on wages and occupational choices. To make progress separating the two race-specific barriers from each other, one needs additional restrictions on racial skill gaps associated with the tasks.

Model Implication 4: Task-specific taste-based discrimination in a given period (δ^{taste}_{bkt}) can be identified empirically using the above procedure for tasks where there are no racial skill gaps (i.e., $\eta_{bkt} = 0$). In the last portion of the paper, we will use this model implication to isolate taste-based discrimination for one particular task. In particular, we use detailed micro data to show that $\eta_{bkt} \approx 0$ for one of our task measures. For this task, we will be able to attribute all of our estimated race-specific barrier to δ^{taste}_{bkt}.

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 how task-specific racial barriers have evolved over time.

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) and Deming (2017) using the DOT data. Below, we provide a brief summary of these measures. The last task measure is new and was created specifically for this paper to help get at the concept of taste-based 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 the intensity of taste-based discrimination is likely to be the most salient.

We now briefly summarize our task measures with additional discussion in the appendix:[13]

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, textile sewing machine operators, dressmakers, x-ray technology specialists, meter readers, pilots, drafters, auto mechanics, 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 fire fighters, drivers (taxi, bus, truck), skilled construction (e.g, electricians, painters, carpenters) and landscapers/groundskeepers.

[13]Our goal is to stay as close as possible to the definitions of task measures developed by others so as to provide new evidence on the racial differences in these measures. However, in the online appendix, we show that the racial differences in the task content of occupations that we highlight are very similar using alternative task definitions.

Contact: measures the extent that the job requires the worker to interact and communicate with others (i) within the organization or (ii) with external customers/clients or potential customers/clients. To create our measure of *Contact* tasks we use two 1998 O*NET work activity variables taken from Deming (2017). 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.[14] Occupations with high measures of *Contact* tasks include various health care workers, waiter/waitress, sales clerks, lawyers, various teachers, and various managers.

The occupational task measures are available at the 3-digit occupational code level. We use Deming (2017)'s crosswalk to merge these measures to our samples from the other data sets we use. 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 the appendix, we report the task requirements of many 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 (2017)). However, recent work has suggested that there are important changes within occupations with respect to the extent that various tasks are required (see, for example, Atalay et al. (2020) and Cavounidis et al. (2021)). We highlight a series of exercise in the appendix showing that our key results are robust to our baseline assumption that the task content of occupations is constant over time. The are two reasons why our main results

[14] In the online appendix, we separately show the evolution of racial gaps in two sub-components of our *Contact* task measure.

are do not change when we allow the task content of occupations to vary over time. First, empirically, the task content of occupations in z-score units are relatively constant across the DOT samples. We highlight the persistence of the task content of occupations in the appendix. Second, and more importantly, the extent to which there are differences over time in the task composition of an occupation does not alter our estimates of racial task gaps. In particular, our key descriptive facts highlighted in this section remain relatively unchanged when we allow for the task content of occupations to evolve across the DOT samples.

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. 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 Black and White 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 results shown in Figure 1 of the introduction.[15]

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

[15] Spitzer (2018) highlights that Black men are disproportionately missing from household surveys relative to White men. Developing a procedure to account for the selected differential coverage between Black and White men in household surveys, Spitzer (2018) recomputes measures of Black-White wage gaps. While accounting for missing Black men in households surveys affects somewhat the level of the racial wage gap, it does not meaningfully affect the magnitude of the trend in the racial wage gap over time. Given all of our results are based off of the trends, our results are similar regardless of whether or not we adjust our measures of racial wage gaps for the potential of missing Black men in the Census/ACS data.

and White men:

$$\tau_{iot}^{k} = \alpha_t^k + \lambda_t^k Black_{it} + \sum_{s \neq k} \omega_{st}^k \tau_{iot}^s + \Gamma^k X_{it} + \epsilon_{iot}^k, \tag{6}$$

where τ_{iot}^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).[16] To isolate the racial difference in tasks, we also control for the occupational content of the other tasks.[17] 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 2 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.

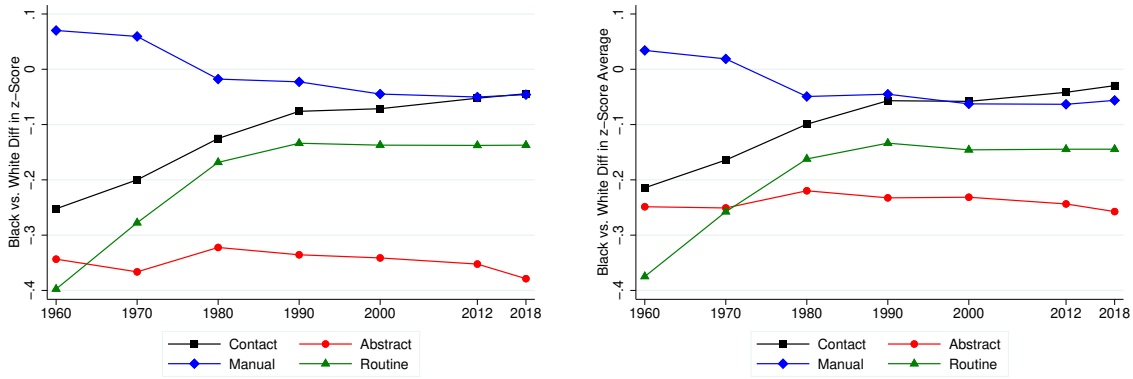
Figure 2 shows that both the level difference in racial task gaps in 1960 and the subsequent time series trend differ markedly by task. The differences are especially pronounced when we compare the racial gaps in *Abstract* and *Contact* tasks. In the early 1960s, Black workers were systematically underrepresented 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 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 2000 and widened slightly after 2000, 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.

To facilitate comparison with our wage regressions below, we also estimate the following

[16] Our model does not include the individual's choice of years of schooling prior to entering the labor market. As a result, we calibrate 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 calibrate the model using data on racial wage and task gaps conditional on education.

[17] In the online appendix, we show the raw trends in the τ_{iok}^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 Differences in the Task Content of Occupations



Panel A: No Controls

Panel B: With Controls

Notes: Figure shows the estimated λ_{kt}'s from the regression specified in equation (7). 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 are 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.

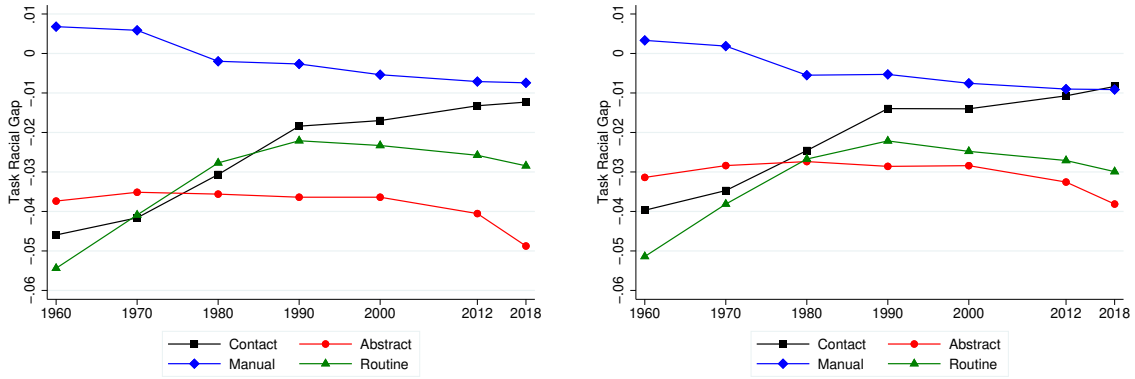
specification to isolate changes in racial task gaps over time. The findings are nearly identical to what we show in Figure 2 except that the racial task gaps are expressed in different units. In particular, we estimate:

$$Black_{iot} = \alpha_t + \sum_k \lambda_{kt}\tau^k_{iot} + \Gamma_{kt}X_{it} + \epsilon_{iot}. \tag{7}$$

where τ^k_{iot}, $Black_{iot}$ and X_{it} are defined as above. Our coefficients of interest are again the λ_{kt}'s, which inform the change in the proportion of Black workers associated with a one standard deviation increase in task k requirements in year t, holding all other task requirements fixed. Each yearly regression yields four λ_{kt}'s – one for each of our four task measures. Figure 3 plots these coefficients. As seen from the figure, the time series patterns are identical to what we show in Figure 2. According to these regressions, in 1960 a one-standard deviation increase in the *Abstract* task contents of an occupation reduced the probability that an individual working in that occupation was Black by about 3 percentage points conditional on education. The patterns in Figure 3 will be used to calibrate the composite task-specific racial barriers ($\eta_{kt}+\delta^{taste}_{kt}$) in our structural model.

Our model of occupational choice is static. In Figure 4, we re-estimate equation (7) separately for various 10-year birth-cohorts in each of the sample years. This allows us to

Figure 3: Racial Differences in the Task Content of Occupations, Alternate Specification



Panel A: No Controls

Panel B: With Controls

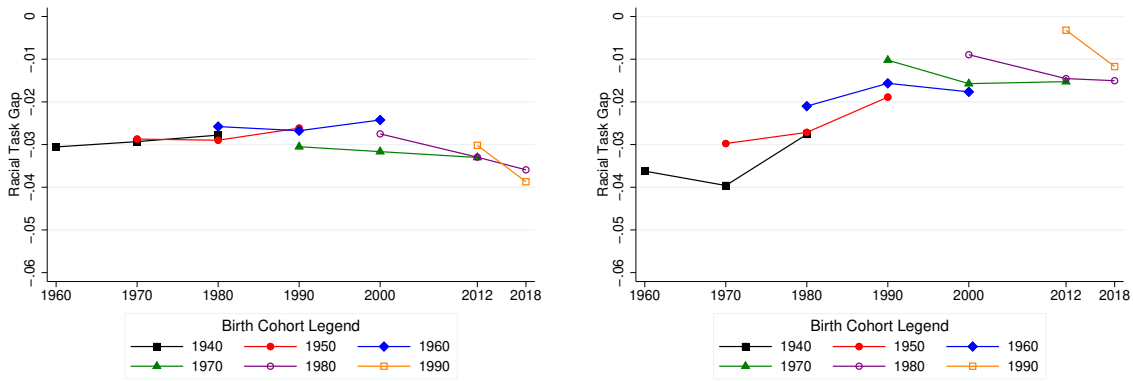
Notes: Figure shows the estimated λ_{kt}'s from the regression specified in equation (7). The coefficients provide an alternate measure of the racial gap in the task content of occupations. Sample restricted to native born individuals between the ages of 25 and 54 within the Censuses and ACS years who are not self-employed and who are 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 0.001 for all tasks in all years.

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.[18] 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.

Before concluding 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 are discussed in the online appendix. 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, the convergence in the *Contact* tasks was much stronger among individuals with less than a bachelor's degree. These results highlight that our main findings about the time series patterns in racial task gaps are not being driven by the educational requirement

[18]For much of the paper, we highlight differences between *Abstract* and *Contact* tasks. The racial gap in *Manual* tasks is close to zero and has little trend over time. The racial gap in *Routine* tasks narrowed partially up to 1980 and then diverged slightly thereafter.

Figure 4: Racial Differences in the Abstract and Contact Content of Occupations, By Birth Cohort



Panel A: Abstract Task

Panel B: Contact Task

Notes: Figure shows the estimated λ_{kt}'s from the regression specified in equation (7) separately for each 10 year birth-cohort. For example, the 1940 cohort is defined as those individuals born between 1935 and 1944. Sample is the same as in Figures 2 and 3.

of the occupations associated with the task.[19]

3.4 Time Series Changes in Task Returns

As noted in our theoretical model, the value-added from using a task-based approach to understand trends in racial wage gaps is amplified when (1) there exists 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 the Census/ACS data. These regressions will be used to discipline the β_{kt}'s in our model. Particularly, we run:

$$\omega_{iot} = \alpha_t^g + \sum_k \tilde{\beta}_{kt}^g \tau_{iot}^k + \Gamma_{kt}^g X_{it} + \epsilon_{ijt}. \tag{8}$$

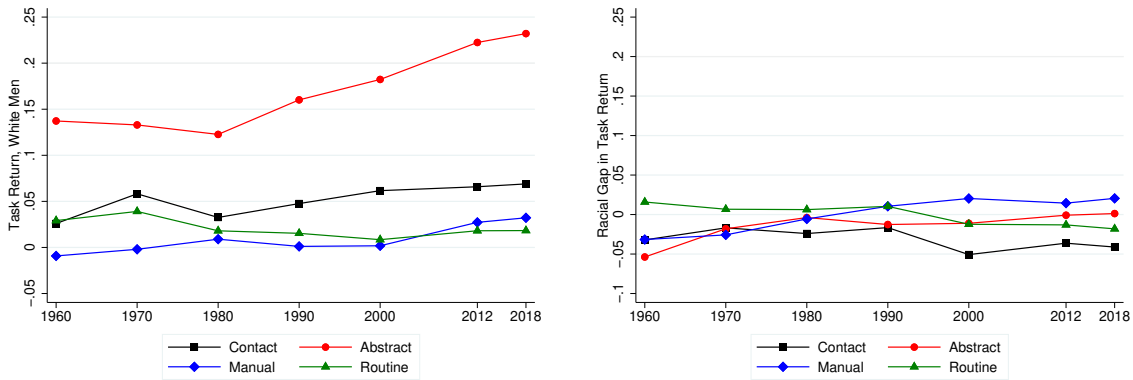
where ω_{ijt} is the log wage of individual i working in occupation j during year t. Our coefficients of interest are the $\tilde{\beta}_{kt}^g$'s, the Mincerian wage premium of task k in year t for group g.

[19]This paper focuses on labor market differences between Black and White men. The appendix, however, also documents differences in task measures between White men and White women, as well as differences between White women and Black women. Like their male counterparts, the gap in *Abstract* tasks between Black and White women remained essentially constant since 1960. Further, the gap in *Contact* tasks between Black and White women narrowed substantively between 1960 and 2018. We choose to focus on Black and White men so as to abstract from the large trends in female labor supply that have also occurred during this time period.

For this regression, we use our sample of full-time workers.

Figure 5 reports estimates of the raw wage premium by task requirement for White men (Panel A) and the demographically-adjusted Black-White gaps in the wage premium by task requirement (Panel B). Three main findings emerge from this figure. First, the average wage premium of *Abstract* tasks for White men was about 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 has increased steadily thereafter. This increase in the return to *Abstract* tasks has received lots of attention in the literature. Second, in contrast, the wage premium associated with the other tasks were notably lower in the early 1960s and have not changed much since then. Finally, the racial gaps in the wage premiums to tasks are relatively small and roughly constant over time.

Figure 5: Mincerian Task Premiums, White Men and Racial Gap



Panel A: White Men, No Controls

Panel B: Racial Gap, With Controls

Notes: Figure shows the average labor market return to occupational task content for White men in Panel A using our primary Census/ACS samples with the additional restriction that individuals report working at least 48 weeks during the prior year. This panel shows coefficients from a regression of log wages on the four task measures, separately by year without age and education dummies. Panel B shows the racial gap in average task returns of Black men relative to White Men conditional on education and age.

4 Explaining the Stagnation of the Black-White Wage Gap Post-1980

In this section, we first discuss how we use the above empirical patterns to discipline the key driving forces of our theoretical framework. Then, we use our estimated structural model to

explore the role of changing task returns in explaining the evolution of the Black-White wage gap since 1960.

4.1 Model Calibration and Estimation

To estimate and calibrate the baseline model, we proceed in two steps. First, we use the micro data from O*Net and DOT combined with the occupational sorting and occupational earnings of *White men* described above to discipline the key race-neutral parameters governing occupational and task sorting (the β_{kt}'s and the A_{ot}'s). We estimate these race-neutral driving forces separately for each year of our Census/ACS samples. Second, we use *racial differences* in occupational sorting, task returns and aggregate wages to pin down the composite race-specific driving forces for each task in each year ($\eta_{bkt} + \delta_{kt}^{taste}$). The logic of the procedure is straightforward. Given the structure of our model, labor market data on White men pins down the race neutral aggregate forces in the model while differences between Black and White men pin down the race-specific barriers. Table 1 lists the key parameters of the model and data moments used to help discipline the parameters. We now provide more details.

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*.[20]

The model for White men ($g = w$) is given by equations (3), (4), and (5) along with the normalization that $\delta_{kt}^{taste} = 0$ and $\eta_{kt} = 0 \; \forall \; k$ and t. The skill endowment ϕ_{ik} follows a Frechet distribution with shape θ and a scale parameter of 1, both of which are constant over time and across racial groups.[21] Likewise, the occupational preference ν_{iot} follows a Frechet distribution with shape ψ and a scale parameter of 1, both of which are constant over time and across racial groups. Given the distributions are constant over time and groups, we omit the time and group subscripts from the ϕ's and ν's. We outline how we set θ and ψ below. However, taking these parameters as given, the remaining parameters to be estimated each year for White men are: A_{ot}'s for $o = 1, ..., O$ in each year t; A_{wHt} in each year t (the productivity in the home sector for White men); and the β_{kt}'s for $k = 1, ..., 4$ in each year t.

We estimate A_{ot}'s, A_{wHt} and β_{kt}'s in each year by targeting (i) the average log income of White men in each occupation in each year;[22] (ii) employment share of White men in each

[20] As we discuss in the online appendix, 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. We construct $\tau_{o1}, ..., \tau_{oK}$ for the model from the z-scores by linearly projecting the z-scores of task content to the unit interval [0, 1]. This change of units is otherwise innocuous given that the β_{kt}'s will be scaled accordingly to pin down the level of wages.

[21] We normalize the location ϕ_k^{min} of the Frechet distribution to zero. This has no effect on our estimates of key driving forces β_{kt}'s and $\delta_{kt} + \eta_{kt}$'s since occupation effects A_{ot}'s absorb ϕ_k^{min}'s.

[22] When estimating the model, we follow the procedure in Hsieh et al. (2019) by aggregating occupations to 66 broad occupation categories; the broad occupation categories we use come from the Census occupation

Table 1: Model Parameters and Data Targets

Panel A: Common Across Race Groups		
Parameter	Variation	Data Target
τ_{jk}'s	Occupational task demands	ONET/DOT Data
β_{kt}'s	Task scaling factors	Mincerian task returns, White men Aggregate task content, White men
A_{jt}'s	Occupational marginal revenue product	Occupational shares, White men Occupational earnings, White men
ψ	Shape parameter occupational tastes	Labor supply elasticity
θ	Shape parameter task skills	Variance of log earnings, White men
Panel B: Varies Across Race		
$\eta_{gkt} + \delta^{taste}_{gkt}$	Composite race-specific task barrier	Aggregate racial wage gap Aggregate racial gap in task contents Race gap in empirical task returns
$A_{g,H,t}$	Racial home sector preference	Share full time employed by race

Notes: Table lists key model parameters and data moments used to discipline the parameters.

occupation in each year; (iii) employment share of White men in the home sector in each year; (iv) the empirical price of each task for White men in each year (shown in Figure 5 Panel A); and (v) the aggregate content of each task for White men in each year.[23] These last two moments help pin down the β_{kt}'s while the first two moments help pin down the A_{ot}'s for the market occupations. We compute the mean of squared deviations in each of (i) and (ii), as well as the sum of squared deviation in (iii)-(v), and search for the set of parameter values that minimizes the sum of these numbers.

The Frechet shape parameters θ and ψ are estimated from the average within-occupation variation in log income and the labor supply elasticity for White men, respectively. Intuitively, a smaller θ translates to a higher degree of heterogeneity in skill endowments ϕ_{ik}'s

sub-headings in 1990.

[23]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_{gHt}'s to match the actual shares in the home sector for White and Black men separately by year.

among workers in the same occupation (for given employment shares) and therefore a higher variance in log earnings within each occupation; 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 discuss in detail the mapping of the model parameters θ and ψ to these data moments in the online appendix. Chetty et al. (2013) suggests the extensive margin elasticity of labor supply of about 0.25; the average of the within-occupation variance in log earnings for White men (weighted by employment shares) is about 0.27 in the 1990 Census. We estimate these shape parameters using the 1990 data and apply the estimates to all years. We choose a value of $\theta = 6$ and a value of $\psi = 4.5$ to roughly match these targets.[24]

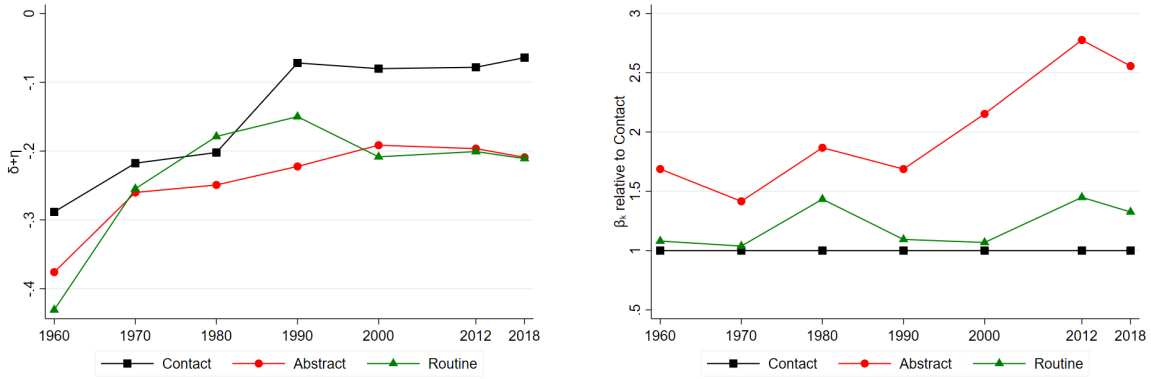
In the second step, after we estimate the A_{ot}'s, the β_{kt}'s, ψ, and θ, we estimate the *composite* race specific term $(\delta^{taste}_{bkt} + \eta_{bkt})$ for each k. We do so by targeting (i) the conditional racial gaps in aggregate task contents, (ii) the conditional racial gaps in task premiums (for each task k), and (iii) the conditional aggregate wage gap. Specifically, we target (i) the coefficients obtained from regressing $Black_{iot}$ on task contents τ^k_{iot} with individual controls for age, education and Census division (Panel B of Figure 3), (ii) the Black-White difference in the Mincerian wage premiums on tasks (Panel B of Figure 5), and (iii) the conditional aggregate wage gap presented in Figure 1. We minimize the weighted sum of squared deviations, where we weight the aggregate task content gaps more heavily than the task price and wage gaps in order to match the sorting pattern closely.

One exception with our estimation strategy is with the *Manual* tasks. Because the empirical wage premium on *Manual* tasks for White men is close to zero, the first step of our model calibration estimates that $\beta_{Manual,t} = 0 \; \forall \; t$. Consequently, the composite racial barriers $(\delta^{taste}_{bkt} + \eta_{bkt})$ for *Manual* tasks contribute neither to overall racial wage gaps nor to sorting given the model structure. Hence, we focus on estimating the η_{bkt}'s and δ_{bkt}'s 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.

Appendix Figure A9 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 fits the data on racial gaps in tasks and wages very well. Furthermore, realizing that the quantitative exercises we explore below rely on the functional form assumptions we made for the various distributions from which individuals draw task-specific skills and preferences, we explore in Appendix Figure A10 whether such distributional assumptions are grossly at odds with the data by assessing the extent to which our estimated model matches other

[24] We discuss the robustness of our key results to alternate values of θ and ψ in the online appendix. As highlighted in the appendix, our key quantitative results are quite robust to alternate values of θ and ψ.

Figure 6: Model Estimates of $\eta_{bkt} + \delta_{bkt}^{taste}$ and Relative β_{kt}'s



PANEL A: TRENDS IN $\eta_{bkt} + \delta_{bkt}^{taste}$ PANEL B: ESTIMATES OF RELATIVE β_{kt}'S

Notes: Panel A of figure shows model generated estimated $\eta_{bkt} + \delta_{bkt}^{taste}$ for *Abstract*, *Contact*, and *Routine* tasks across years. Panel B shows the estimates of the relative β_{kt}'s. In particular, we plot the relative β_{kt}'s of *Abstract* and *Routine* tasks relative to the β_{kt} for *Contact* tasks in the same year.

non-targeted moments. 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 replicates nearly identically 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 well a variety of non-target moments gives us confidence in the quantitative exercises we highlight next.

4.2 The Stagnation of the Racial Wage Gap Post 1980

In this subsection, we show the estimates of the race-neutral and race-specific driving forces in our structural model. Then, we use the estimated model to explain the convergence of the racial wage gap between 1960 and 1980 and its stagnation thereafter.

Panel A of Figure 6 shows the estimated trend of the sum of $(\eta_{bkt} + \delta_{bkt}^{taste})$ for Black men in the the *Abstract*, *Contact*, and *Routine* tasks. Given the model, these are the implied racial differences in a combination of mean task-specific human capital levels (the η_{bkt}'s) and taste-based discrimination measures (the δ_{bkt}^{taste}'s) for each task. The model says that the combined $\eta_{bkt} + \delta_{bkt}^{taste}$ term explains both racial differences in occupational sorting and racial differences in the returns to task k in year t. As seen in the figure, there was a reduction in the composite term $\eta_{bkt} + \delta_{bkt}^{taste}$ for all three tasks between the 1960s and 2018.

Panel B of Figure 6 shows the estimated trends in relative β_{kt}'s for the various task

measures.[25] In particular, we show the estimates of β_{kt}'s for *Abstract* and *Routine* tasks relative to the β_{kt} for *Contact* tasks during the same year. The figure shows that the task prices for *Abstract* tasks have been rising relative to the task prices of other tasks, particularly after 1980. As we discussed in Section 2.6, our model implies that, given relatively high and persistent barriers to *Abstract* tasks faced by Black men, a relative increase in the return to *Abstract* tasks disadvantages Black workers and widens the racial wage gap.

Figure 7 quantifies the extent to which these estimated changes in race-neutral and race-specific 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 — A_{ot}'s, β_{kt}'s, $\delta_{kt}^{taste} + \eta_{kt}$'s, and A_{gHt}'s — 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.[26] The exercise allows us to understand how the respective forces – including the rising return to *Abstract* tasks – contributed to the stagnation of the racial wage gap post-1980.

In particular, the red line (with circles) in Panel A of Figure 7 shows the contribution of the race-neutral driving forces (β_{kt}'s and A_{ot}'s) to the evolution of the racial wage gap between 1980 and 2018. The exercise shows that the race-neutral driving forces *widened* the racial wage gap by 6.3 log points over over the 1980-2018 period, where the racial wage gap in 1980 was 23.9 log points. Given that $\beta_{Abstract}$ 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. The black line (with squares) in Panel A of the figure shows the flip side of our analysis; it isolates the contribution of the composite race-specific forces (the $\delta_{bkt}^{taste} + \eta_{bkt}$'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 *narrowed* the racial wage gap by 6.5 log points during this period, where the racial wage gap in 1980 was 23.9 log points.[27]

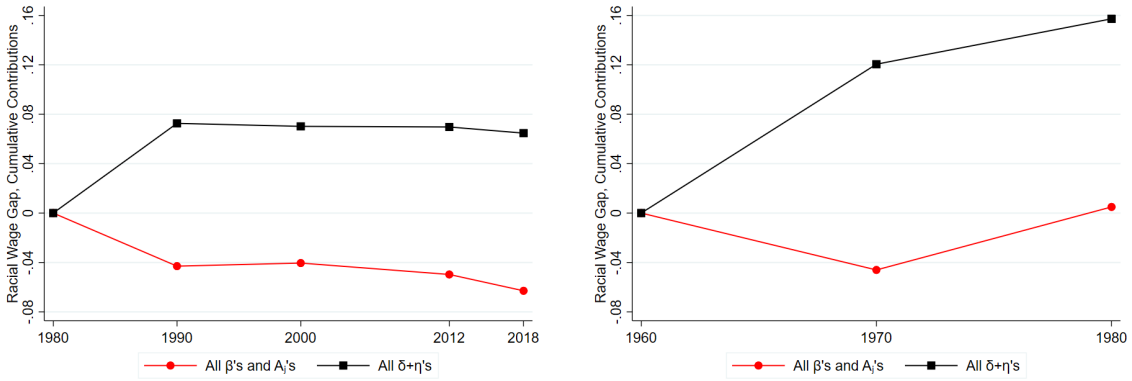
In sum, the model suggests that the racial wage gap has remained relatively constant since 1980 because of two offsetting effects. On the one hand, a combination of declining discrimination and a narrowing of racial skill gaps reduced the racial wage gap between 1980 and 2018 by about 6.5 percentage points - with most of the effect occurring between 1980 and 1990. On the other hand, changes in race neutral forces such as the increasing return to *Abstract* tasks widened the gap by about 6.3 percentage points during the same period. Because Black workers face barriers associated with sorting into occupations that

[25] The level of the estimated β_{kt}'s are shown in the appendix.

[26] See the appendix for the formal derivations of this quantitative exercise.

[27] The relative trend over time in the racial gap in the A_{gH}'s is small in our estimated model; it widened the racial wage gap just by 0.5 log points over the 1980-2018 period. Given the small quantitative importance, we relegate most of our discussion of these trends to the online appendix.

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 A_{jt}'s) and race-specific forces ($\delta_{kt}^{taste} + \eta_{kt}$'s) to the evolution of the racial wage gaps over the 1980 to 2018 period (Panel A) or over the 1960 to 1980 period (Panel B).

require *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 combined to keep the racial wage gap relatively unchanged between 1980 and 2018.[28]

Panel B of Figure 7, on the other hand, shows that changes in task and occupational returns had little effect on the evolution of the racial wage gap between 1960 and 1980. In particular, changing task and occupation returns hardly affected the racial wage gap over the 1960-1980 period. Instead, the racial wage gap was entirely driven during this period by an improvement in the race-specific δ_{kt}^{taste}'s and η_{kt}'s. Our model, therefore, is consistent with the vast literature showing that forces such as the Civil Rights Act had a large effect on improving the relative labor market outcomes of Black men during the 1960s and 1970s. The reason that changing task returns had little effect on the racial wage gap during the 1960-1980 period is because all of the task returns evolved roughly similarly during this period. Post-1980, in contrast, the return to *Abstract* tasks rose relative to all other tasks and Black men faced high and persistent barriers in these tasks.

[28]In the appendix, we also show that the relatively constant racial gap in the *Abstract* task content of occupations between 1980 and 2018 is also the product of two offsetting forces. On the one hand, a decline in race-specific barriers narrowed the gap in *Abstract* tasks between Black and White men. However, simultaneously, the rising return to *Abstract* tasks drew relatively more White men into occupations requiring these tasks thereby increasing the racial Abstract task gap.

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

Our structural model provides a road map to empirical researchers looking to uncover changing race-specific factors ($\delta_{bkt}^{taste} + \eta_{bkt}$) in micro data. In particular, the model suggests – as highlighted in proposition 4 – that one must control for changes in the return to different tasks when analyzing the evolution of Black-White wage differences over time. We use panel data from the 1979 and 1997 waves of National Longitudinal Survey of Youths (NLSY) to implement this theory guided empirical specification.

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 the online appendix.

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

$$\omega_{it} = \alpha^0 + \alpha_t^1 D_t Black_i + \sum_k \alpha_{kt}^2 D_t \bar{\tau}_{ki} + \Gamma X_{it} D_t + \mu_i + \epsilon_{it} \tag{9}$$

where again ω_{it} is the log wage of individual i from the NLSY in period t and $\bar{\tau}_{ik}$'s are the average task contents of the occupations individual i worked in during their life. We compute the $\bar{\tau}_{ik}$'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 $\bar{\tau}_{ik}$'s – to evolve over time; note that the individual average task measures are interacted with time dummies. 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 con-

Table 2: The Evolution of Racial Wage Gaps Over Time in the NLSY: The Importance of Controlling for Time-Varying Task Returns

	(1)	(2)	(3)	(4)
Racial Wage Gap: 1990s	0.002	0.020	0.037	0.038
	(0.022)	(0.019)	(0.019)	(0.019)
Racial Wage Gap: 2000s	0.051	0.034	0.083	0.086
	(0.028)	(0.032)	(0.032)	(0.033)
Racial Wage Gap: 2010s	0.029	0.026	0.080	0.081
	(0.038)	(0.039)	(0.040)	(0.041)
Demographic Controls * Year Dummies	Yes	Yes	Yes	Yes
Individual Fixed Effects	No	Yes	Yes	Yes
Abstract Task Content * Year Dummies	No	No	Yes	Yes
Other Task Content* Year Dummies	No	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.

trols 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 age and education dummies again interacted with time dummies. 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 2. 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 our standard demographics. 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. In column 2, we include individual fixed effects; we still find no trend in racial wage gaps between 1980 and 2018. Omitted individual time-invariant factors thus cannot explain the stagnation in Blacks' relative wages over the last 40 years.

Once we control for the rising return to *Abstract* tasks over time, however, we find a strong convergence in racial wage gaps post-1980. Specifically, in column 3, we control for

time-varying return 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 8 log points in the 2000s and 2010s. The results are nearly identical when we additionally control for time-varying returns to *Contact*, *Routine*, and *Manual* tasks (column 4). As suggested by our model, conditioning out the effects of time-varying tasks returns – the rising return to *Abstract* task in particular – unveils the convergence in the racial wage gap due to changing race-specific factors. Strikingly, the magnitude of the convergence we estimate in the NLSY between 1980 and 2018 once properly controlling for the changing returns to skills (column 4 of Table 2) is very similar to the magnitude we estimate from our structural model (Panel A of Figure 7).

The above findings also highlight why our estimated model yields quantitatively different conclusions regarding the extent to which race-specific factors have improved in the United States during the last forty years relative to a popular statistical decomposition method developed by Juhn et al. (1991) (henceforth known as JMP). In the online appendix, we perform the JMP decomposition on our data from the Census/ACS and show that the decomposition dramatically understates the importance of both skill price changes in widening the racial wage gap and declining race specific factors in narrowing the racial wage gap over the 1980-2018 period relative to our model. This is because the JMP procedure assumes that White workers with a given wage perform a similar mixture of tasks as Black workers with the same wage. In our multi-task model with selection, that assumption does not hold; a White worker with a given wage is more likely to have sorted into occupations with high *Abstract* task requirement than a Black worker with the same wage. These appendix results highlight the quantitative importance of accounting for selection with multiple tasks when decomposing the effect of changing task returns versus changes in race specific barriers on racial wage gaps.

6 Pre-Labor Market Skills and the Task Content of Occupational Sorting

We now use our model to explore our conjecture that the racial gap in *Contact* tasks is informative about the extent of taste-based discrimination in the economy. According to our model, if the racial gap in skills used to perform *Contact* tasks is close to zero in each period (i.e., $\eta_{Contact,t}$=0), then our above estimates of the race specific barrier for *Contact* tasks ($\delta^{taste}_{Contact,t} + \eta_{Contact,t}$) isolates both the level and the trend in taste-based discrimination. In this section, we use additional data from the NLSY to examine the extent of racial differences

in the pre-labor market skills that are associated with *Contact* tasks.

6.1 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. We summarize these measures briefly here and include a more detailed discussion in the appendix.

Cognitive Skills (COG): We follow the literature and use the respondent's standardized 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.[29]

Non-cognitive Skills (NCOG): We use the measures of non-cognitive skills created by Deming (2017). Deming (2017) 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.[30] Likewise, for the NLSY97 cohort Deming (2017) 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 (2017)'s non-cognitive skill measures are expressed in z-score units.

Social Skills (SOC): We again follow Deming (2017) 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

[29]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 (2017). We follow Altonji et al. (2012) to generate age-adjusted AFQT scores.

[30]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.

questions so they have the same scale and then average them together. We then convert the measures into z-score units. Deming (2017) 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).

6.2 Racial Gaps in Pre-Labor Market Skills

Table 3 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 that were working. 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 gaps in non-cognitive and social skills are relatively small and constant over time.[31]

6.3 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:

$$\overline{\phi}_{wokt} = a_{kt} + b_{cog,kt}\overline{S}^{NLSY}_{cog,wot} + b_{ncog,kt}\overline{S}^{NLSY}_{ncog,wot} + b_{soc,kt}\overline{S}^{NLSY}_{soc,wot} + \epsilon_{wokt}, \tag{10}$$

[31] 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 3: 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	-1.01	-0.96	-0.80	-0.62
	(0.03)	(0.04)	(0.03)	(0.05)	(0.06)	(0.05)
(B) Non-Cog. Skills	-0.20	-0.19	-0.10	-0.12	0.06	0.16
	(0.04)	(0.04)	(0.04)	(0.05)	(0.07)	(0.07)
(C) Social Skills	-0.09	-0.11	-0.09	-0.17	-0.15	-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	3,702	3,702	2,354	1,870	1,870
Sample Size Observations	4,226	22,479	22,479	2,354	7,923	7,923

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.

where the dependent variable $\overline{\phi}_{wokt}$ is the occupational-average of observed task-specific skills ϕ_{wokt} for White men w working in occupation o in period t generated by the model, and the regressors are the empirical measures of average cognitive ($\overline{S}^{NLSY}_{cog,wot}$), non-cognitive ($\overline{S}^{NLSY}_{ncog,wot}$) and social traits ($\overline{S}^{NLSY}_{soc,wot}$) for White men in the corresponding occupations from our sample of NLSY respondents. 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. 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 use the estimated weights for White men and the Black-White gap in measured individual pre-labor market traits from the NLSY to impute the racial gaps in task-specific skills in each occupation. Define $\overline{S}^{gap}_{cog,ot}$, $\overline{S}^{gap}_{ncog,ot}$, and $\overline{S}^{gap}_{scog,ot}$ as the racial gaps in NLSY measures of cognitive, non-cognitive, and social skills in each occupation,

respectively. Formally, using the coefficients from the first stage regression ($\hat{b}_{cog,kt}$, $\hat{b}_{ncog,kt}$, and $\hat{b}_{soc,kt}$), we predict racial gaps in task-specific skills $\overline{\phi}^{gap}_{okt}$ – whose predicted values we denote with $\widehat{\phi}^{gap}_{okt}$ – in each occupation based on the racial gaps in the NLSY skills:

$$\widehat{\phi}^{gap}_{okt} = \hat{b}_{cog,kt}\overline{S}^{gap}_{cog,ot} + \hat{b}_{ncog,kt}\overline{S}^{gap}_{ncog,ot} + \hat{b}_{soc,kt}\overline{S}^{gap}_{soc,ot}. \tag{11}$$

Once we obtain the NLSY-based predictions, we infer the η_{bkt}'s that make the model-generated $\overline{s}^{gap}_{okt}$'s consistent with the NLSY-based predicted $\widehat{s}^{gap}_{okt}$'s. In sum, our procedure just ensures the model estimate of 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 task-specific barriers facing Black men to taste-based discrimination (δ^{taste}_{bkt}'s) after accounting for racial skill differences (η_{bkt}'s).

6.4 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 (10) for our first stage regression, we use cross occupational variation aggregating the data to 66 unique broader occupations within each year.

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 long run trends in δ^{taste}. To this end, we use the fact that the racial task gaps in the South Census region of the U.S. in 1990 were similar to the racial task gaps in the entire U.S. in 1960. Specifically, the demographically adjusted racial gap in *Contact*, *Abstract*, and *Routine* task content of occupations for the U.S. as a whole in 1960 were, respectively, -0.040, -0.031, and -0.051 (see Panel B of Figure 3). The corresponding values for individuals living in the South region in 1990 Census/ACS data were -0.041, -0.045, and -0.044 (see Panel A of Figure 8). Relative to the observed time series trends over the 1960-2018 period, these values are relatively close to the 1960 national levels. Given this, for our 1960 decomposition, we (i) load the average occupational efficiency units in 1960 on the average occupational skill levels of White men in the South in 1990, and then (ii) use racial differences in skill levels in the South in 1990 as a proxy for racial skill differences nationally in 1960.

Given that the estimated b's are relatively constant over time when we estimate equation (10) separately by year, the first part of our assumption for the 1960 projection is not overly restrictive. The stronger assumption is that the observed racial gap in skills in the NLSY in the South for the 1979 cohort is a good proxy for the racial gap in skills for the country as

Table 4: First Stage Regression of Average Model Task Skills on Average NLSY Individual Skills, Cross-Occupation Variation

	Abstract	*Contact*	*Routine*
Cognitive	0.16	0.04	-0.02
	(0.03)	(0.01)	(0.02)
Non-Cognitive	0.05	0.02	0.01
	(0.03)	(0.02)	(0.03)
Social	-0.02	0.12	-0.10
	(0.05)	(0.03)	(0.03)
Year Fixed Effects	Yes	Yes	Yes
Adj. R-Squared	0.41	0.37	0.07
F-Stat	20.8	9.8	4.6

Notes: Table shows estimate coefficients from first stage regression equation (10) 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 from 1960, 1990, and 2012 so that each regression will have 198 observations (3*66). See the text for additional details.

a whole 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 both cognitive test scores and occupational sorting for men in the NSLY79 cohort are roughly similar to the Black-White gaps in cognitive test scores and occupational sorting for the U.S. as a whole in 1960 gives us some confidence in using our imputation procedure to infer 1960 relationships.

Estimates from our first stage regressions are shown in Table 4. We pool together data from multiple years and estimate (10) assuming each of the b_{kt}'s to be constant over time.[32] The table reports the first stage mapping for *Abstract* (column 1), *Contact* (column 2) and *Routine* tasks (column 3). Each column reflects the estimates of $b_{cog,kt}$'s, $b_{ncog,kt}$'s, and $b_{soc,kt}$'s from separate regressions of equation (10) for the various tasks. A few things are of note from Table 4. First, cognitive skills are most predictive of the skills required for *Abstract*

[32]We do, however, allow the a_{kt}'s to differ across t's. Our assumption that the b_{kt}'s are constant over time was made to increase power. When we allowed the b_{kt}'s to vary over time, the coefficients did not change much across the years but the standard errors increased.

tasks. Occupations where NLSY workers have high cognitive skills on average are also the occupations where the model predicts that workers have higher levels of *Abstract* task-specific 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 unrelated to the skills required for *Abstract* tasks and are negatively related to the skills required for *Routine* tasks. Third, our first stage procedure has large 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.[33]

6.5 Discussion

Before turning to our decomposition results, we end this section by discussing how any misspecification in our decomposition equations (10) and (11) can bias our estimates of the change in our estimated task-specific η_{bkt}'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 $\Delta\eta_{bkt}$ between two periods will be biased. Both within the main paper and in the appendix, we perform various exercises to assess whether such omitted skills could be an issue. We highlight two such exercises here.

First, in Table 2 above, we exploit the panel structure of the NLSY and show that controlling for unmeasured traits by including individual fixed effects hardly affects the estimated changes in the racial wage gap over time (compare columns 1 and 2 of Table 2). This suggests that time invariant omitted individual skills play little role in the evolution of the racial wage gap over the last forty years. Second, in the appendix, we examine whether the labor market returns to pre-labor market traits differ between Black and White men in the NLSY. We find that the labor market returns to social skills are similar between Black and White men. This finding is consistent with there being no differential bias between Black and White men with respect to predicting *Contact* task efficiency from measured traits. On the other hand, consistent with the findings in Neal (2006), the wage return to cognitive skills is higher for Black

[33] In the online appendix, we show additional results where we use the NLSY micro data to map individual pre-labor market traits to the task requirements of their adult occupations. These reduced form results are consistent with the findings in Table 4. In particular, individuals who had relatively more cognitive skills when young were more likely to sort into occupations that required relatively more *Abstract* tasks when older. Likewise, individuals who had relatively more social skills when young were more likley to sort into occupations that required relatively more *Contact* tasks.

men than for White men with the same occupation and education. This is suggestive of the possibility that missing traits associated with *Abstract* tasks differ systematically between Black and White men.

Overall, these results give us some confidence that changing racial gaps in omitted skills are not biasing our estimates of the $\Delta\eta_{bkt}$ and $\Delta\delta^{taste}_{bkt}$ for *Contact* tasks. This is crucial because most of our key model findings in the next section hinge on our estimates of the $\Delta\eta_{bkt}$ and $\Delta\delta^{taste}_{bkt}$ for *Contact* tasks being unbiased. It being a pivotal concern for our paper, we provide additional reassurance in the next section by showing how state-level survey-based measures of taste-based discrimination correlate with our measures of racial gaps in *Contact* tasks.

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

In this section, we discuss the results of our decomposition of the racial barrier in *Contact* tasks into the part due to "taste-based" discrimination (δ^{taste}) and the part due to racial differences in skills (η). We then use external data sources to provide further evidence that that racial gap in *Contact* tasks is a good proxy for taste-based discrimination. We end this section with a discussion of the extent to which taste-based discrimination can explain changes in the racial wage gap over time.

7.1 Decomposing Racial Gaps in *Contact* Tasks

Panel A of Table 5 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 4; these are the same values as the ones shown in black line (with squares) in Figure 6. The second row reports our decomposition procedure's estimate of $\eta_{Contact,t}$ while the final row reports our estimates of $\delta^{taste}_{Contact,t}$.

A few key results are notable with respect to our decomposition for *Contact* tasks. First, our model attributes over two-thirds of the racial gap in *Contact* tasks in 1960 to taste-based discrimination, δ^{taste}; 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, taste-based discrimination associated with *Contact* tasks fell sharply. Essentially all of the decline in the composite racial barrier for *Contact* tasks (21 percentage points) can be attributed to the decline $\delta^{taste}_{Contact,t}$ (19 percentage points). By 2012, the model estimates only a small amount of remaining taste-based discrimination in *Contact* tasks.

Table 5: 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
$\delta^{taste} + \eta$	-0.29	-0.07	-0.08	0.21	-0.38	-0.22	-0.20	0.18
η	-0.08	-0.07	-0.06	0.02	-0.26	-0.23	-0.16	0.10
δ^{taste}	-0.21	0.00	-0.02	0.19	-0.12	0.00	-0.04	0.08

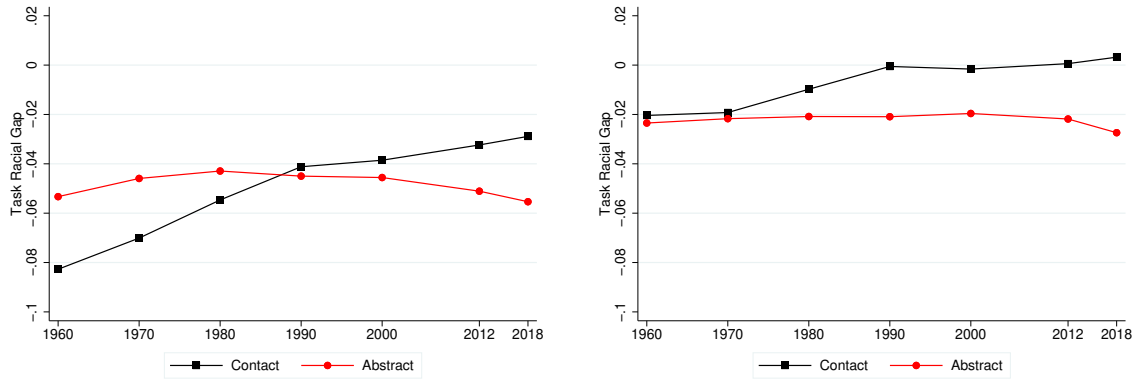
Notes: Table shows model decomposition of racial differences in $\delta_{bk}^{taste} + \eta$ into its components for *Contact* tasks (Panel A) and *Abstract* tasks (Panel B) in 1960, 1990, and 2012 using our decomposition procedure.

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. That racial gap in skills associated with *Contact* tasks explains most of the remaining task-specific barrier in 2012.

These results closely reflect the racial gaps in the NLSY skills and the mapping between the NLSY skills and model-implied task-specific skills we outlined above. First, recall that the NLSY measures of social traits are most predictive of skills required for *Contact* tasks and that the racial gap in social traits in the NLSY is small in all years. Consequently, our procedure implies that racial differences in average *Contact* skills cannot be the primary explanation for the racial barrier associated with *Contact* tasks. Second, according to the NLSY data, cognitive traits (AFQT) also have modest predictive power for skills required for *Contact* tasks. Given that there is a large racial gap in cognitive traits, our procedure also 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. Specifically, changing $\eta_{Contact}$ only explains 2 percentage points out of the 21 percentage point change in the composite racial barrier for *Contact* tasks between 1960 and 2012. Putting the results together, we conclude that changes in the racial gaps in *Contact* tasks over time is a good proxy for changes in taste-based discrimination ($\delta_{Contact}^{taste}$) over time.

As way of comparison, Panel B of Table 5 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 and (ii) there are large racial gaps in cognitive skills

Figure 8: Census/ACS Task Content of Occupations: South Region vs Other Regions



Panel A: South Region

Panel B: All Other Regions

Notes: Figure replicates the analysis in Panel B of Figure 3 separately for individuals residing in the South region (Panel A) and individuals residing in all other regions (Panel B).

among NLSY respondents. Collectively, our decomposition suggests that the racial gap in the sorting into *Contact* tasks is well explained by taste-based discrimination while the racial gap in the sorting into *Abstract* tasks is primarily explained by racial skill gaps.

7.2 *Contact* Task Decomposition and Cross-Region Variation

In this subsection, we exploit cross-region variation to provide further evidence that the racial gap in *Contact* tasks is a good proxy for taste-based discrimination. There is a large body of research documenting that taste-based discrimination was 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 taste-based discrimination, we should expect larger declines in the racial gap of this task measure in the South relative to other regions. Figure 8 replicates the analysis in Panel B of Figure 3 separately for the individuals in the Census/ACS data living in the South region (Panel A) and all other regions (Panel B). Consistent with our conjecture that the racial gap in *Contact* tasks could be a proxy for taste-based discrimination, 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, in both the South and the other regions, there was no racial convergence in *Abstract* tasks over time, though the racial gaps in *Abstract* tasks was always larger in the South.

To further validate our conclusion that racial gaps in *Contact* tasks is a good proxy for

taste-based discrimination, we again exploit cross-state variation to compare racial gaps in *Contact* tasks to survey-based measures of taste-based 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. The GSS asked a nationally representative sample dozens of questions eliciting potential prejudice against Blacks.[34] Focusing on a sample of White individuals, CG create measures of state level prejudice against Blacks.[35] Their measure is standardized with higher values indicating larger levels of taste-based discrimination among Whites within the state.

Panel A of Figure 9 correlates measures of racial gaps in the *Contact* tasks for each state with the CG state-level taste-based discrimination measures. Specifically, for each state we measure the conditional race gap in *Contact* tasks using the specification in equation (7). 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* task content of jobs in 1980 and the CG measure of state-level taste-based discrimination; a simple regression line through the scatter plot yields a slope coefficient of -0.11 (standard error = 0.02) and a R-squared of 0.52. That is, states with high survey-based measures of taste-based discrimination are systematically the states with a larger racial gap in *Contact* task content of jobs.

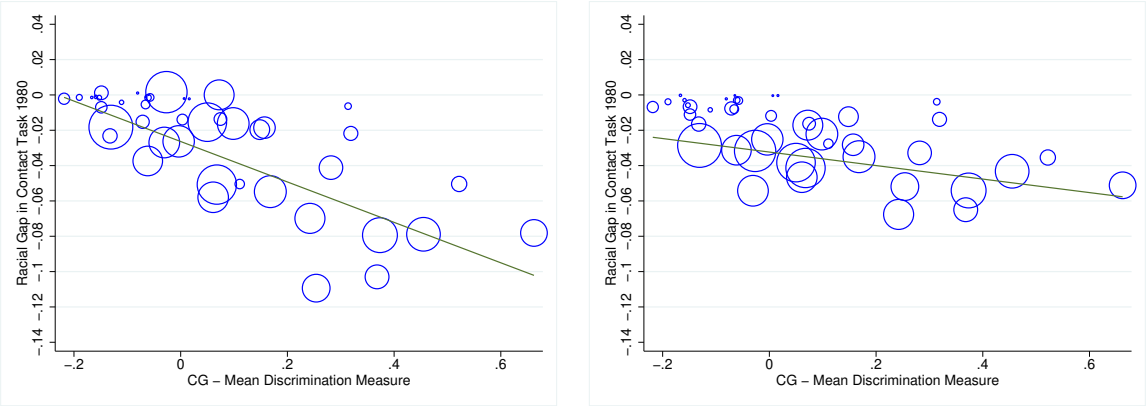
Panel B, on the other hand, illustrates the relationship between the CG measures of taste-based discrimination and state-level gaps in *Abstract* tasks. As seen from this figure, the relationship between survey-based measures of taste-based discrimination and the racial gap in *Abstract* tasks is much weaker than the relationship with the racial gap in *Contact* tasks. In particular, the simple regression line has a slope coefficient of -0.04 (standard error = 0.01) and a R-squared of 0.25. Consistent with our model findings, racial gaps in *Contact* tasks are much more predictive of taste-based measures of discrimination than are *Abstract* tasks. Collectively, these results provide some support for our finding that changes in the racial gaps in *Contact* tasks are informative measures of changing taste-based discrimination.

Stepping outside of our structural model, we can empirically explore other potential evidence that suggests the racial gap in *Contact* tasks is a good proxy for taste-based discrimination. Consider, for example, two locations: one with a large population and one with a small population. Suppose in both locations, Black workers comprise 10 percent of the

[34]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.

[35]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.

Figure 9: Racial Gaps in *Contact* and *Abstract* Tasks vs Survey Measures of Taste-Based Discrimination, State Level Variation



Panel A: Contact Tasks

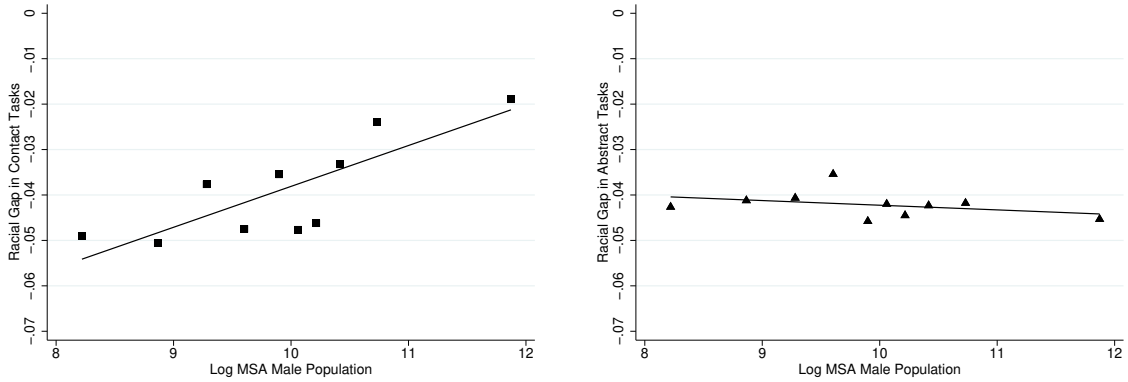
Panel B: Abstract Tasks

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 mean measures of state level prejudice. Racial gaps in the task content of jobs measured using the 1980 U.S. Census. Gaps are conditioned on age and education as in equation (7). 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.

workforce. In the smaller location, scale may be such that any given worker in an occupation that is high in *Contact* tasks must interact with both Black and White customers. In a larger location, scale may be such that any given worker in a occupation that is high in *Contact* tasks may be able to segment such that they only serve either Black or White customers. This is a version of Becker's model of taste-based discrimination where Black workers may be able to sort away from discriminatory employers if scale is sufficiently large. These type of stories would imply that the observed racial gap in *Contact* tasks should be smaller in locations with larger scale.

Figure 10 shows evidence for this prediction. In the left panel, we plot a bin scatter of the relationship between log MSA male population (on the x-axis) and the racial gap in *Contact* tasks (on the y-axis). For this figure, we pool our Census samples over the combined 1960-1990 period to ensure we have enough power to create racial task gaps for both *Contact* and *Abstract* tasks. We further restrict our sample to only analyze the 196 MSAs were there were at least 200 employed Black men between the ages of 25 and 54 in the underlying micro data. As seen from the figure, the racial gap in *Contact* tasks is smaller in MSAs that have larger population. This is consistent with Black men being able to sort away from the discrimination when the size of the market is large enough. Notice, in the right panel, we do not see a similar positive relationship between the racial gap in *Abstract* tasks and the size of the population. Overall, these patterns provide additional supportive evidence that the

Figure 10: Racial Gaps in *Contact* and *Abstract* Tasks vs Log Population, Bin Scatter of Cross-MSA Variation



Panel A: Contact Tasks

Panel B: Abstract Tasks

Notes: Figure shows a bin scatter plot of MSA-level conditional racial gaps in the *Contact* task content of jobs (Panel A) and the *Abstract* task content of jobs (Panel B) against the log of MSA level male population. Task gaps are conditioned on age and education as in equation (7). For power at the MSA level, we pool our primary Census data over the combined years of 1960-1990. We restrict our analysis in this figure to the 196 MSAs where there were at least 200 employed Black men in the pooled 1960-1990 Census samples. For each panel, we have one racial task gap and one log population for the pooled period for each MSA. The bin-scatter is made using ten bins with equal MSA population in each bin.

racial gap in *Contact* tasks is proxying for taste-based discrimination.

7.3 Taste-Based Discrimination and the Racial Wage Gap

In Table 6, we use the model to assess how much of the *change* in the racial wage gap between two periods can be attributed to our estimates of declining taste-based discrimination for *Contact* and *Abstract* tasks. The table extends the exercise in Figure 7 inferring the contribution of the composite race-specific barriers (the $\delta_{bkt}^{taste} + \eta_{bkt}$'s) to the evolution of racial wage gap. In particular, for each task k, we decompose the total contribution of the composite race-barrier (the $\delta_{bkt}^{taste} + \eta_{bkt}$) over the 1960-1970, 1970-1980, and 1980-1990 periods into respective contributions of δ_{bkt}^{taste} and η_{bkt} based on how much of the total change in $\delta_{bkt}^{taste} + \eta_{bkt}$ over the 1960-1990 period comes from a change in δ_{bkt}^{taste} versus a change in η_{bkt}.[36] We perform the decomposition similarly for the 1990-2000, 2000-2012, and 2012-2018 periods based on the estimated relative trends in δ_{bkt}^{taste} versus η_{bkt} over the 1990-2012 period.[37]

[36] Said differently, we perform the linear interpolation assuming that the relative speed of the decline in δ_{bkt}^{taste} versus η_{bkt} is the same across all periods between 1960 and 1990.

[37] The decomposition for 2012-2018 involves a linear extrapolation of the estimated relative changes in δ_{bkt}^{taste} versus η_{bkt} over the 1990-2012 period.

We then compute the cumulative contributions over the 1960-1980 and 1980-2018 periods.

Table 6: Contribution of Various Forces to Changing Racial Wage Gaps Over Time

	1960-1980	1980-2018
Baseline Change in Racial Wage Gap	0.162	-0.003
δ_{bkt}^{taste} for *Contact* tasks	0.033	0.059
δ_{bkt}^{taste} for *Abstract* tasks	0.028	-0.001
η_{bkt} for *Abstract* and *Contact* tasks	0.009	0.014
$\delta_{kt}^{taste} + \eta_{bkt}$ for *Routine* tasks	0.088	-0.007
β_{kt}'s and A_{ot}'s	0.005	-0.063

Note: Table shows the contribution of various model driving forces in explaining the change in the racial wage gap between 1960 and 1980 (column 1) and between 1980 and 2018 (column 2).

According to our fully estimated model, declining taste-based discrimination for *Contact* tasks contributed 3.3 percentage points to the decline racial wage between 1960 and 1980 (row 2, column 1) and contributed 5.9 percentage points to the decline in the racial wage gap between 1980 and 2018 (row 2, column 2). Summing the results over the combined 1960 to 2018 period, we find that declining taste-based discrimination estimated for *Contact* tasks contributed nearly 60 percent of the decline in the racial wage gap during the last sixty years in the United States (0.092/0.156). Our combined estimates of taste-based discrimination for both *Contact* and *Abstract* tasks (combining the second and third row) contributes over three-quarters to the evolution of the racial wage gap between 1960 and 2018 (0.119/0.156).

Rows 4, 5 and 6, respectively, show the contributions to the change in the racial wage gap associated with (i) the estimated racial skill gaps for *Abstract* and *Contact* tasks, (ii) the combined racial barriers for *Routine* tasks, and (iii) the effect of the race neutral barriers. The last row just restates the findings shown in red lines (with circles) in Figure 7. Rows 2 through 6 essentially sum to row 1; any small remaining differences is due to the contribution to the racial wage gap associated with changes in the in relative preferences for the home sector between Black and White men ($A_{wHt} - A_{bHt}$).

8 Conclusion

In this paper, we developed a task-based model to explain differences in occupational sorting and wages between Black and White men over the last sixty years in the United States. We then estimated the model using micro data from the Censuses, American Community Surveys, and the National Longitudinal Surveys of Youths (NLSY) to quantify the contributions of race-neutral and race-specific forces to the evolution of the racial wage gap since 1960.

The paper presents two important quantitative results. First, 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, both narrowing racial skill gaps and declining discrimination post-1980 resulted in the wages of Black men converging to those of White men, 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 discrimination and a narrowing of racial skill gaps; 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.

Second, our paper establishes that the declining racial gap in *Contact* tasks between 1960 and 2018 is a good proxy for declining taste-based 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 taste-based discrimination; our model and data work confirm this conjecture *ex-post*. Specifically, the fact that there are very small racial gaps in social skills – combined with the fact that measures of pre-labor market social skills in the NLSY are highly predictive of subsequent entry into occupations that require *Contact* tasks – implies that racial gaps in *Contact* tasks must stem almost entirely from taste-based discrimination and very little from racial skill differences. Our model thus implies that the changes in racial gaps in *Contact* tasks over time is a good proxy for changes in taste-based discrimination. 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 taste-based discrimination, while state-level racial gaps in *Abstract* tasks correlate with them only weakly.

While there was a narrowing in racial skill gaps over time, we estimate that large racial skill gaps remain. We want to stress that these racial gaps in skills are themselves endogenous and subject to discrimination. Current or past levels of taste-based discrimination are almost certainly responsible for Black-White differences in measures of cognitive test scores. Such caveats should be kept in mind when trying to segment current racial wage gaps into parts due to taste-based discrimination and parts due to differences in market skills. To the extent that we identify taste-based 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 skill gaps associated with a given task, the existence of such gaps imply that changes in 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.

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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 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. We exclude from our sample anyone who is living in group quarters (keep gq = 1) 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. The files also contain measures of cognitive ability, personality traits, and sociability. We follow a large body of research, including Neal and Johnson (1996), Heckman et al. (2006), Altonji et al. (2012) and Deming (2017), and aggregate these measures into three categories (i) cognitive, (ii) non-cognitive, and (iii)

social skills. These measures are taken directly from (Deming, 2017). 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 are proxied using the Armed Forces Qualifications Test (AFQT). This measure is available for both the NLSY79 and the NLSY97 waves. 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 (2017) normalized these to have mean zero and standard deviation one. We use his measures for all of our analysis.

While both the NLSY79 and the NLSY97 include AFQT scores, these waves contain different measures of non-cognitive and social traits. Deming (2017) provides a set of unified measures of non-cognitive and social skills which we adopt. Specifically, the Deming definition for non-cognitive skills uses (i) the normalized average of the Rotter Locus of Control and the Rosenberg Self-Esteem Scale (see Heckman et al. (2006)) in the NLSY79 wave and (ii) the Big-5 factor conscientiousness, normalized and standardized, in the NLSY97 wave. The Deming definition for social skills uses (i) an average of four self-reported normalized and standardized measures, including sociability at age 6, sociability in 1981, number of clubs each respondent participated in high school, and participation in high school sports in the NLSY79 wave and (ii) an average of two items, normalized and standardized, that capture the extroversion factor from the Big-5 personality test in the NLSY97 wave.

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 (2017). For all questions we use from both surveys, we follow Deming (2017) 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 (2017) 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 (2017) 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 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 (2017) 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 (2017), 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 (2017). Specifically, we use the variables *Job-Required Social Interaction (Interact)* and *Deal With External Customers (Customer)*.[38] *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 (2017) are available at the 3-digit occupational code level. We use Deming (2017)'s crosswalk to merge these measures to (i) the Census and the Amer-

[38] Deming (2017)'s focus is creating a measure of occupational tasks that require social skills and document how the returns to social skills have increased over time. His measure of social skills include measures of whether the job requires the worker to have social perceptiveness and the ability to coordinate, persuade and negotiate with others. For example, his measure of social skills includes O*NET questions assessing whether the job requires "adjusting actions in relation to others' action", "being aware of others' reactions and understanding why they react the way they do", and "persuading others to approach things differently". His measure of social skills do not include measures for whether the task requires interactions with other co-workers or customers. He uses the measures of customer (*Customer*) and broader social interactions (*Interact*) as controls in some of his specifications. These questions are much more suited to our purpose of trying to measure taste-based discrimination. We explore the relationship between Deming's *Social Skills* task measure and our *Contact* task measure in the online appendix.

ican 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.

Appendix A.4 Task Composition of Selected Occupations

Appendix Table A1 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).

Table A1: 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	1.01	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	0.14	-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 A2 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. We create measures of the Contact task content of each occupation using the 1998 O*Net data. Panel A of the table shows the correlation in the various underlying occupational task measures using the 1977 and 1991 DOT data. Panel B of the table shows the correlation in various underlying occupational task measures using the 1998 and 2018 O*NET data. As a reminder, all tasks are measured in cross-occupation z-score units. For example, a task content of an occupation equal to 1 for task k implies that the occupation has an occupational task content for task k that is 1 standard deviation higher than the average occupation.

In Panel A, we show the persistence between 1977 and 1991 DOT occupational task contents. We show the persistence for the five underlying questions that comprise the Abstract, Routine and Manual task measures. As seen from the table, there is an extremely large occupational task persistence for all five of our underlying task measures: *GED-Math*, *DCP*, *FINGDEX*, *STS*, and *EYEHAND*. The simple bi-variate R-squared's from all of the regressions range between 0.84 and 0.98.

In Panel B, we show the persistence between the 1998 and 2018 O*NET occupational task contents. We show the persistence for the two underlying questions that comprise our Contact task measure: *Interact* and *Costumer*. We explore the persistence of two other measures in the O*NET that others have used to measure *Abstract* and *Routine* tasks. Specifically, we show the persistence in two O*NET questions asking (i) the extent to which an occupation requires mathematical reasoning (which we call *Math Reasoning*) and (ii) the extent to which the job is automated (which we call *Automated*). These questions have been used by others as inputs into alternate measures of the Abstract and Routine task content of an occupation

Table A2: Persistence of Occupational Task Content Over Time

Panel A: 1977 DOT vs. 1991 DOT		
	Coefficient (S.E.)	Adjusted R-Squared
GED-Math	1.00 (0.01)	0.98
DCP	0.92 (0.01)	0.90
FINGDEX	0.96 (0.01)	0.92
STS	0.94 (0.02)	0.84
EYEHAND	0.94 (0.02)	0.91
Panel B: 1998 O*NET vs. 2018 O*NET		
	Coefficient (S.E.)	Adjusted R-Squared
Interact	xxx (xxx)	0.xx
Customer	xxx (xxx)	0.xx
Math Reasoning	xxx (xxx)	0.xx
Automated	xxx (xxx)	0.xx

Notes: Panel A shows the results of a regression of the task-content of an occupation as measured in the 1977 DOT (in z-score units) on the task-content of that same occupation as measured in the 1991 DOT (in z-score units). We run such regressions separately for various task measures. The panel reports the regression coefficient on the 1991 DOT occupational task measure (column 1) as well as the regressions Adjusted R-squared (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 (in z-score units) on the task content of that same occupation as measured in the 2018 O*NET (in z-score units). Each regression in this panel has xxx occupations. Otherwise the structure of the results in this panel are symmetric to what is shown in Panel A. Standard errors in parentheses.

created using O*NET data (see, for example, Deming (2017)). Like with the DOT data between the 1977 to 1991 period, the occupational task measures in the O*NET data are highly persistent over time.

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 overtime. 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 on 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 documented in the main text to alternate specifications. Finally, we show the racial task gaps separately for different education groups.

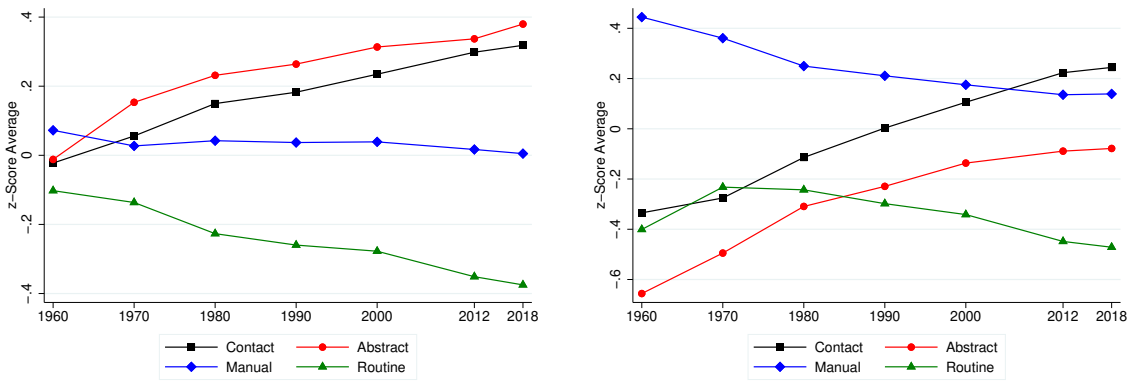
Appendix B.1 Raw Occupational Task Sorting, By Race

Appendix Figure A1 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 A1 reports the coefficients on the year dummies (β_t^g) from the following regressions using our individual Census/ACS data:

$$\tau_{iogt}^k = \sum_t \beta_t^g D_t + \epsilon_{iogt} \tag{A1}$$

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 two groups g: White men and Black men. As a result, all coefficients have g superscripts. We explore the four tasks k highlighted in the main text. 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, β^g_t are plotted in the figure.

Figure A1: Raw Task Trends: White and Black Men



Panel A: White Men

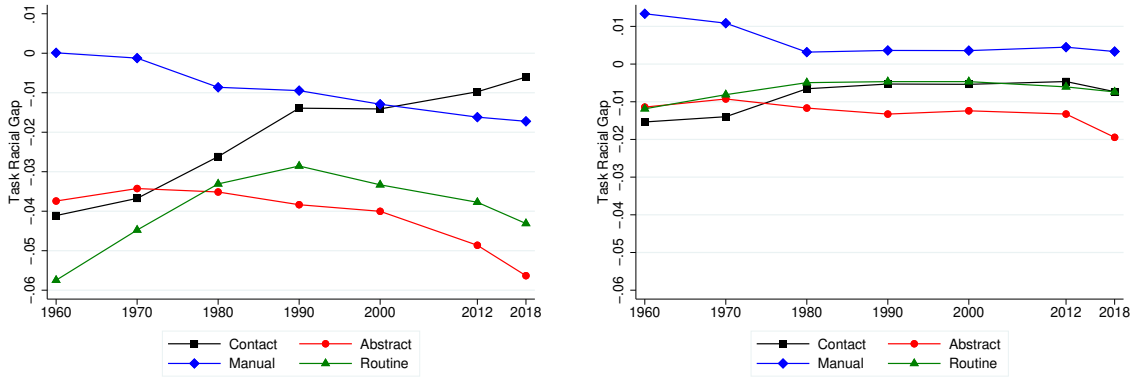
Panel B: Black Men

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. Regressions are run separately for White men (Panel A) and Black men (Panel B) and were weighted using Census/ACS individual sampling weights.

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 A2 redoes the main results of Figure 3 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 slight divergence in *Abstract* tasks. The magnitude of the *Contact* convergence is

Figure A2: Race Gap in Tasks: By Educated Groups



Panel A:
Less than a Bachelors Degree

Panel B:
Bachelors Degree or More

Notes: Figure re-estimates Panel B of Figure 3 of the main text separately by those with less than a bachelors degree (Panel A) and those with a bachelors degree or more (Panel B).

much larger for less educated individuals, but given selection (Panel A represents between 70 and 75 percent of the sample depending on the year), it is not surprising that the convergence in *Contact* tasks is smaller for higher educated individuals.

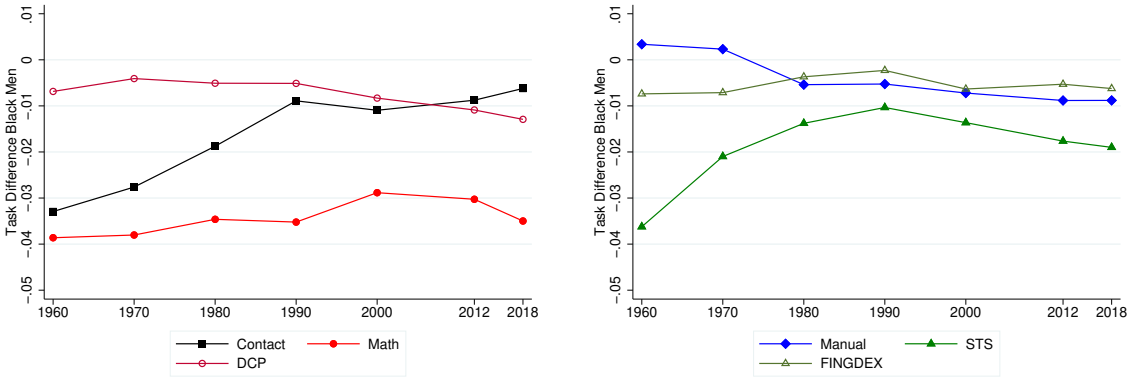
Appendix C Robustness of Racial Task Gaps: Alternate Task Definitions

In this section, we explore the robustness of our results to alternate task definitions. We begin by disaggregating our current task measures into their separate task components. We then explore the racial gaps in alternate definitions of four main task categories. Finally, we compare our *Contact* tasks measure to Deming (2017)'s *Social* task measure. As seen in this section, our results are quite robust to alternate task definitions.

Appendix C.1 Decomposing Task Measures into Sub-Components

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*).

Figure A3: Race Gap in Tasks: Disaggregated Task Measures



Panel A Panel B

Notes: Figure re-estimates Panel B of Figure 3 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.

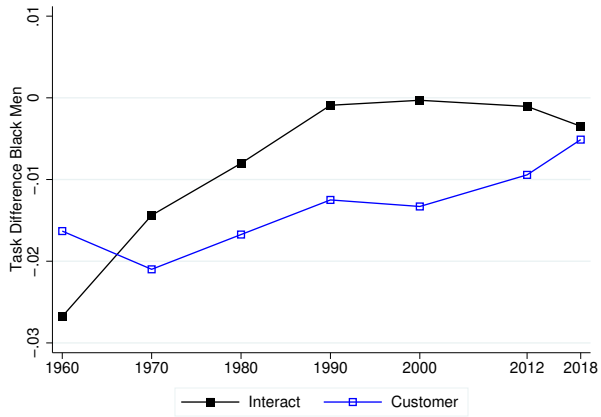
In particular, we re-estimate the results in Panel B of Figure 3 using six task measures instead of four. The sample used is the same as in Panel B of Figure 3 of the main text. The coefficients on the task measures from these yearly regressions are plotted in Appendix Figure A3. We plot the coefficients 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 constant through 2018. However, Blacks made large gains in *Contact* tasks over this time period.

Appendix Figure A4 shows the results from the regression but with seven tasks measures. We still include *GED-Math*, *DCP*, *FINGDEX*, *STS* and *Manual*. But, we now disaggregate *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 seven sets of coefficients, we only show the coefficients on *Interact* tasks and *Customer* tasks.[39] 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 forms of contact with others.

[39]The coefficients on the other five tasks were essentially unchanged relative to Appendix Figure A3.

Figure A4: Race Gap in Disaggregated *Contact* Task Measures



Notes: Figure re-estimates Panel B of Figure 3 of the main text with seven 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) *FINGDEX* subcomponents. Finally, 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.

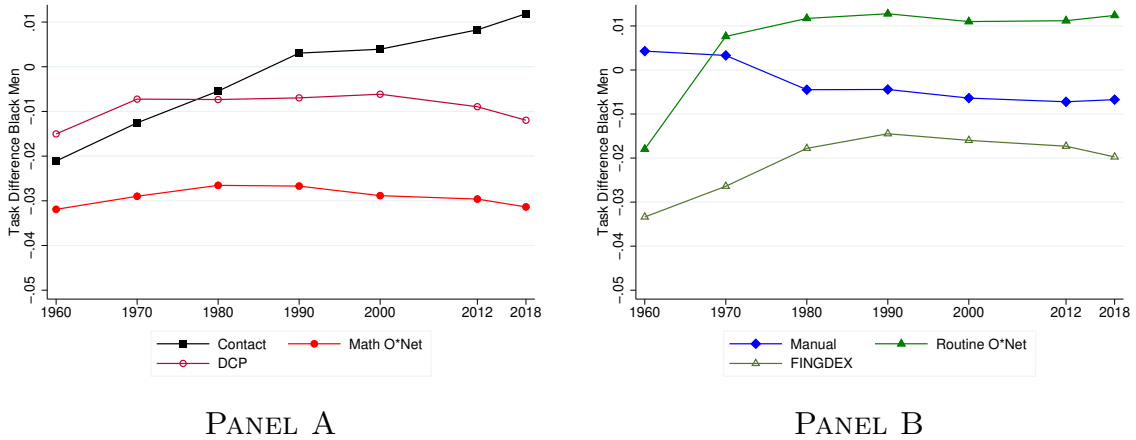
Appendix C.2 Robustness to O*Net Measures of *Math* and *Routine* Tasks

Deming (2017) 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 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.[40] Given this, we treat Deming's

[40]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 A5: Race Gap in Tasks: Alternate Measures of *Routine* and *Math* Task Measures



Notes: Figure re-estimates Panel B of Figure 3 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.

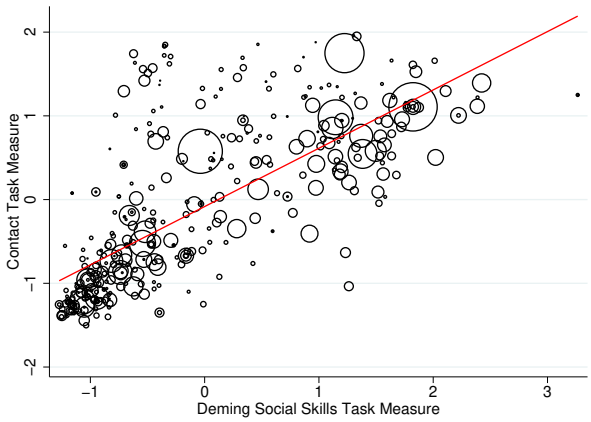
Routine task measure created using the 1998 O*Net data as being an alternative for the *STS* task measure within the DOT data.

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 A3 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 A5. 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

The key finding in our paper is the racial convergence in *Contact* tasks relative to *Abstract* tasks in the U.S. over the last half century. In this sub-section, we explore the sensitivity of our results to using other measures of *Contact* tasks. Deming's *Social Skills* task measure is highly correlated with our *Contact* task measure. This is not surprising given that Deming's measure of *Social Skills* measures whether the occupation requires skills associated with the ability to coordinate, negotiate, and persuade. The ability to coordinate, negotiate, and

Figure A6: Correlation Between *Contact* Task and Social Task, Cross-Occupation Variation



Notes: Figure 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. Each observation in the figure is an occupation. *Contact* and *Social Skills* 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* tasks is 0.70 (standard error = 0.03) and an adjusted R-squared of 0.65.

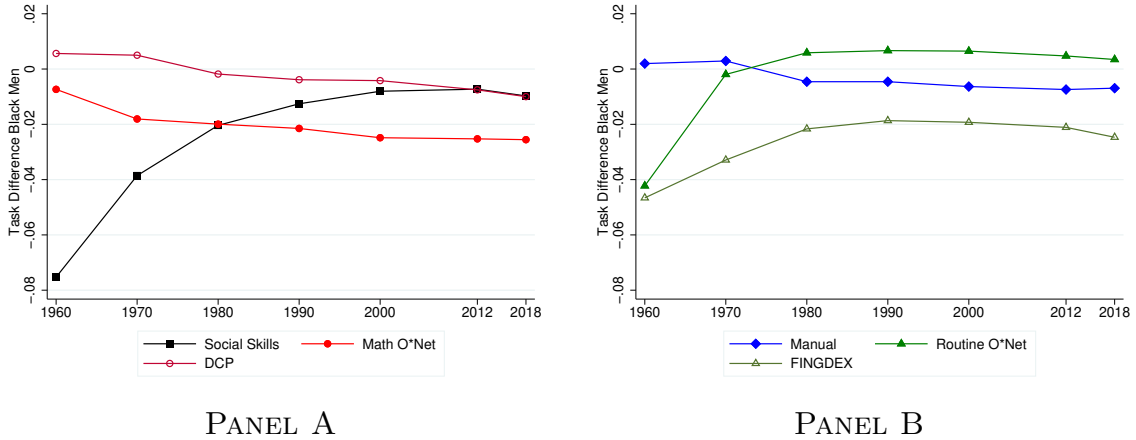
persuade is needed when the job requires workers to come into contact with other co-workers, clients and customers. The simple correlation between Deming's *Social Skills* task measure and our *Contact* task measure is about 0.7 (weighted by 1990 population counts within in each occupation). We show the simple scatter plot by occupation of the two measures in Appendix Figure A6.

Appendix Figure A7 is the analog to Appendix Figure A5 except we replace our *Contact* task measure with Deming's *Social Skills* task measure. As highlighted in Deming (2017), the *Social Skills* task content of an occupation is highly correlated with the *Math* and the *DCP* task content of an occupation. As a result, the racial gap in *Abstract* Skills is smaller and the racial gap in *Social Skills* is larger in 1960. Despite that, our key patterns remain. There was a substantial narrowing of the racial gap in the *Social Skills* task content of an occupation since 1960. When we use this measure, there is also a slight divergence in the task content of the two components of *Abstract* skills. Black men are gaining relative to White men not because of a convergence in *Abstract* tasks but a convergence in tasks that require interactions with others.

Appendix D Task Gaps by Gender

Appendix Figure A8 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

Figure A7: Race Gap in Tasks: Social Skills Tasks



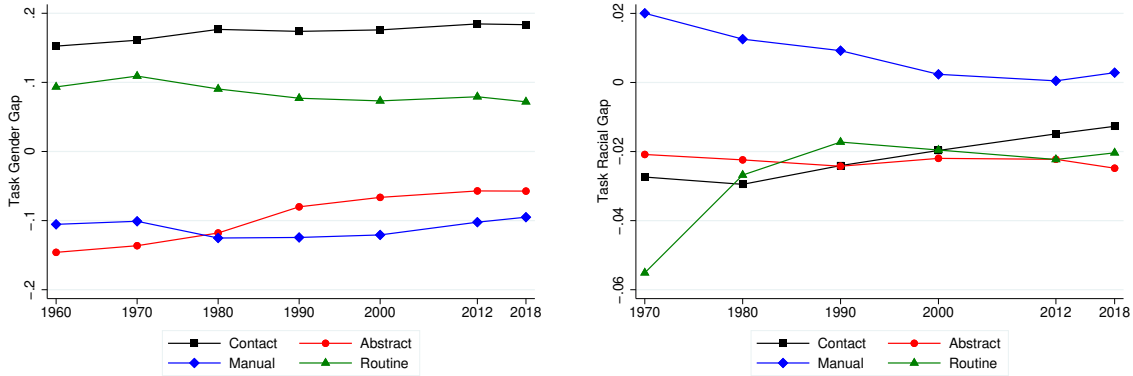
Notes: Figure re-estimates Appendix Figure 3 with six task measures further replacing Deming's *Social Skills* task measure for our *Contact* task measure. As with Appendix Figure A5, we use Deming's measure of occupational *Math* and *Routine* task measures along with our measures of DCP, FINGDEX, and *Manual* tasks.

the Census/ACS. This figure uses the same specification as Panel B of Figure 3 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, women are much more likely to be in *Contact* and *Routine* tasks and are much less likely to be in *Manual* and *Abstract* tasks. 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 were 16 percentage points less likely to work in occupations that require 1 standard deviation higher *Abstract* tasks relative to White men (conditional on age and education). By 2018, that gap fell to 7 percentage points.

The time series patterns in Panel B between White women and Black women mirror the patterns in Panel B of Figure 3 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.

Figure A8: 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 shows the extent to which the task content of an occupation can predict whether an individual employed in that occupation is a White woman (Panel A) or a Black woman (Panel B). For the regressions in Panel A, we use the Census/ACS sample pooling together prime-age White men and women. Panel shows the coefficients from a regression of a dummy variable equal to one if the individual is a White woman on the four task measures and controls for individual education, age and Census division, separately by year. For the regressions in Panel B, we use the Census/ACS sample pooling together prime-age White women and Black women. Panel shows the coefficients from a regression of a dummy variable equal to one if the individual is a Black woman on the four task measures and controls for individual education and age, separately by year. All samples for both regressions are also restricted to full time workers who are not self employed and who are native born.

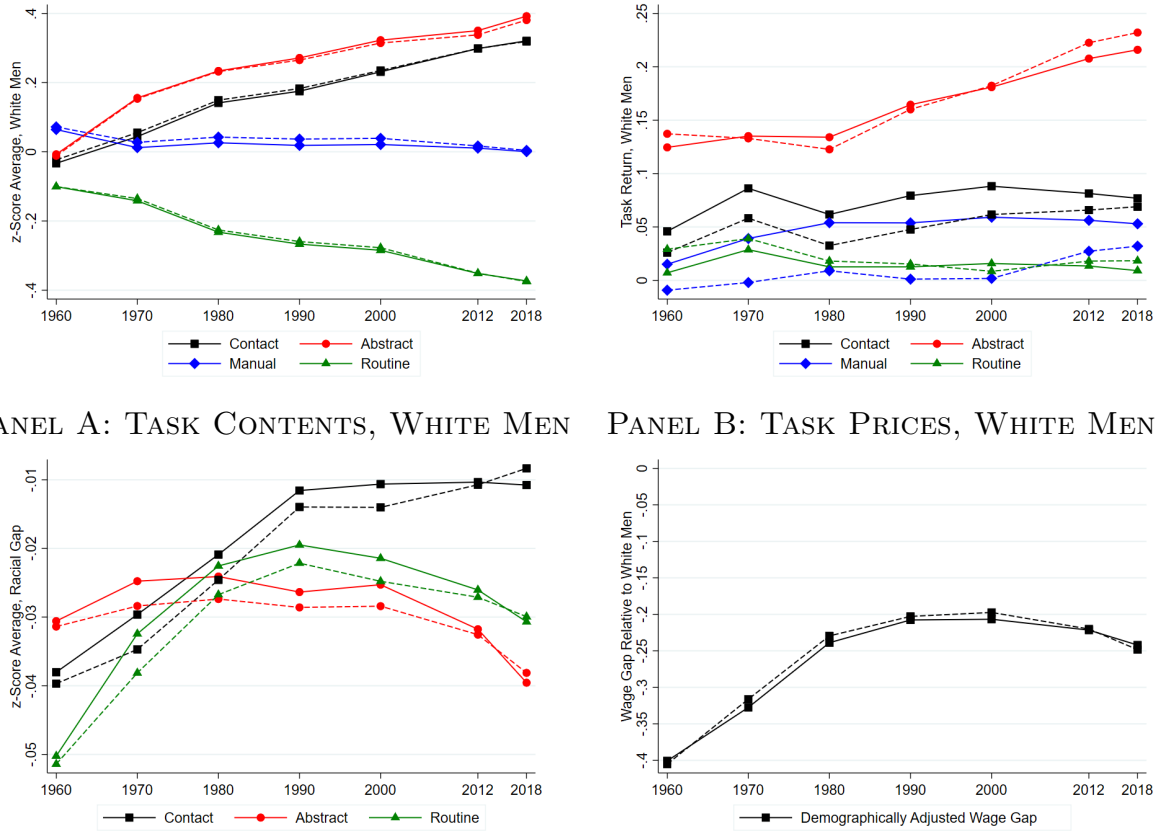
Appendix E Additional Results on Estimated Model Fit and Model Validation

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

Appendix E.1 Model Fit

Figure A9 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. 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 our estimate of $\beta_{Manual,t}$ being equal to zero (which means that racial barriers in *Manual* tasks have no effect on sorting or wages) has little impact on our key paper results.

Figure A9: Model versus Data Moments



Panel A: Task Contents, White Men

Panel B: Task Prices, White Men

Panel C: Task Contents, Gap

Panel D: Aggregate Wage Gap

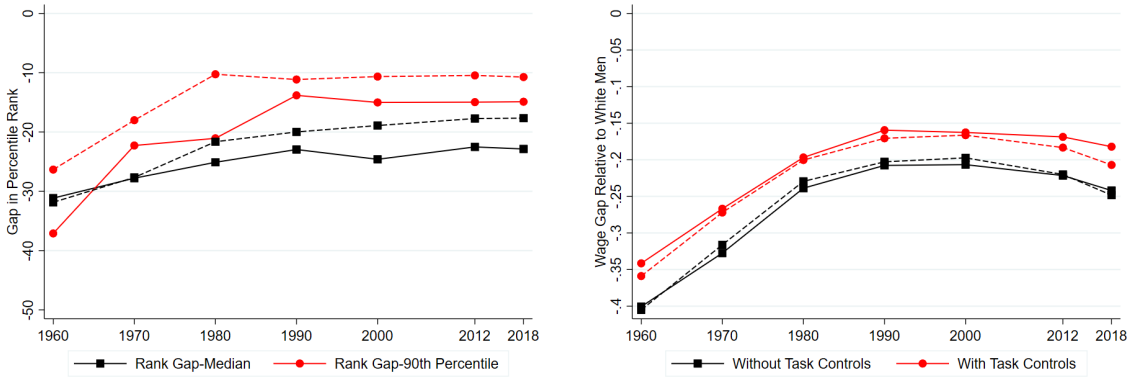
Notes: Figure shows how selected model moments (solid lines) compare to their corresponding data moments (dashed lines). The data moments are the ones used to discipline the model. Panels A and B are data for White Men and are unconditional on education. Panels C and D are the racial gaps in wages and task content of occupations conditional on age and education as highlighted in Figures 1 and 2 to account for these demographic differences between Black and White men.

Appendix E.2 Model Validation

The counterfactuals 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 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 calibrating 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

Figure A10: 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.

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 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 A10 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. Both in 1980 and 2018, the median Black man had wages that was equal to about the 25th percentile of the White wage distribution. Conversely, much more relative progress was made for Blacks at the top

of the 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 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 A10 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 calibrating 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 counterfactuals we highlight next.

Appendix F Comparison of Model-Based Decomposition Method to Juhn-Murphy-Pierce Statistical Decomposition Method

Our estimated model yields quantitatively different conclusions about the extent to which race-specific factors (like a narrowing of racial skill gaps or a decline in discrimination) have improved in the United States during the last forty years relative to what one would conclude with a popular statistical decomposition method developed by Juhn et al. (1991). Juhn et al. (1991) attribute the slowdown of convergence in the racial wage gap to rising skill prices. Central to their analysis is the racial wage *rank* gap, i.e., the position (percentile rank) of Black workers in the White earnings distribution. Specifically, they decompose trends in racial wage gaps into a change in the position of Black workers in the White distribution ("positional" convergence) and a change in the variance of the (White) earnings distribution ("distributional" convergence). Their key insight is that changes in the level of inequality within the White earnings distribution can impact the racial wage gap even if Blacks main-

tained the same position, simply because Blacks and Whites occupy different initial positions in the earnings distribution. In their attempt to distinguish race-specific forces from general forces such as skill price changes, they perform the statistical decomposition of the racial wage gap trends into distributional and positional convergence, and then interpret the former as stemming from trends in skill prices and the latter as proxies for trends in race-specific forces. Such an interpretation is valid in a univariate skill model. In such a model, two workers with the same earnings will have the same underlying levels of aggregate skills, so changes in aggregate skill returns will affect them in the same way. Said differently, White men of a given wage is a good control group to proxy for the unobserved skills of Black men in a model with one aggregate skill price. This means trends in skill prices cause distributional convergence but not positional convergence; hence, when there is only one aggregate skill price, it is correct to attribute positional convergence to trends in race-specific forces.

However, in a multivariate skill model like ours, the distributional convergence fails to capture the full effects of relative skill return changes. This is because White workers with identical initial wages are not a good control group for Black workers. A change in one skill price (relative to other skill prices) can affect two workers with the same initial earnings differently depending on the exact mix of skills they possess ($\eta_{gk} + \phi_{ik}$'s), the level of discrimination they face (δ_{gk}^{taste}'s), as well as the task requirements (τ_{ok}'s) in the occupations they have sorted into. Hence, changes in relative skill (or task) returns can shift the percentile ranks of Black workers in the White earnings distribution therefore also causing positional convergence (or divergence). As we have documented throughout the paper, Black workers have lower *Abstract* skills, face higher discrimination in *Abstract* tasks, and as a result are less likely to be in occupations with high *Abstract* task content. Given that, a rising *Abstract* task return will on average benefit Black workers less than White workers with the same initial earnings and will therefore shift down their relative positions in the earnings distribution. To the extent that this force is ignored, measured distributional convergence understates the impact of the rising *Abstract* task return on the racial wage gap. By the same token, the shifting down of Black percentile ranks in the earnings distribution (due to the rising *Abstract* task return) will dampen any estimated gains Blacks have made in reducing racial wage rank gaps, so the positional convergence will also understate the effects of declining discrimination and narrowing racial skill gaps.

To illustrate the quantitative difference between our model and a model with one aggregate skill price, we compare the estimated effects of changing β's and A_j's and of changing δ's and η's presented in Table 6 to what we would find if we did a Juhn-Murphy-Pierce (JMP) decomposition on the same model-generated data. We perform this comparison during two

Table A3: Model Decomposition vs Juhn-Murphy-Pierce Decomposition

	Change in Wage Gap	Task Model Decomposition		JMP Decomposition	
Time Period	Total	β's/A's	$(\delta+\eta)$'s	Distributional Convergence	Positional Convergence
$1960-1980$	0.162	0.005	0.157	0.034	0.128
$1980-2018$	-0.003	-0.063	0.065	-0.034	0.031

Notes: Table shows counterfactual wage gaps using our task-based model and (separately) using the Juhn-Murphy-Pierce (JMP) decomposition. The first column shows the baseline change in the Black-White wage gap during the given time period. The next two columns decomposes how much of the change in the wage gap is due to the changing β_{kt}'s and A_{jt}'s and how much is due to the changing $\delta_{bkt}+\eta_{bkt}$. These come from our estimated model. The final two columns show the JMP decomposition. The distributional convergence refers to the change in the racial wage gap due to the changing aggregate price of skill throughout the wage distribution, while positional convergence refers to the shifts in the relative positions of Blacks within the White earnings distribution.

time periods: 1960-1980 and 1980-2018.[41] The results of this comparison are shown in Table A3. During the early period, our model based decomposition and the JMP decomposition yield very similar results. This is not surprising given the results in Panel B of Figure 6 showing that there was no differential trend in task prices during the 1960-1980 period. When relative task prices evolve similarly, the implications of a one-skill model and a multi-task model are similar. However, during the post-1980 period, the JMP decomposition dramatically understates the importance of skill price changes in widening the racial wage gap relative to our model. In particular, we find that the changing task prices caused the racial wage gap to increase by 6.3 log points during this period while the JMP decomposition concludes that changing skill prices increased the racial wage gap by roughly half that amount. Because the distributional convergence is understated relative to our model, the JMP model also substantially understates the importance of declining discrimination and the narrowing of racial skill gaps in improving relative Black wages during the last forty years. Collectively,

[41] On the model-side, we fix β_{kt}'s (and A_{jt}'s) or $\delta_{bkt}^{total}+\eta_{bkt}$'s at the levels at the beginning of the period, and report the differences between the counterfactual racial wage gap thus computed and the actual racial wage gap at the end of the period as the estimated effects of changing β_{kt}'s (second column) and $\delta_{bkt}^{total}+\eta_{bkt}$ (third column), respectively. As for the JMP decomposition, we use the model-generated earnings distributions to compute the changes in the percentile rank of each Black worker in the White earnings distribution over each period, and estimate what their wages would have been at the end of the period if the White earnings distribution were fixed at the beginning of the period; the difference between the counterfactual racial wage gap thus computed and the racial wage gap at the beginning of the period gives an estimate for positional convergence (fifth column), while the difference between the actual racial wage gap at the end of the period and the counterfactual wage gap gives an estimate for distributional convergence (fourth column).

the results in Table A3 highlight that analyzing racial wage gaps in a multi-skill task model can lead to quantitatively different conclusions relative to a standard JMP decomposition, particularly in periods when relative task prices are changing.

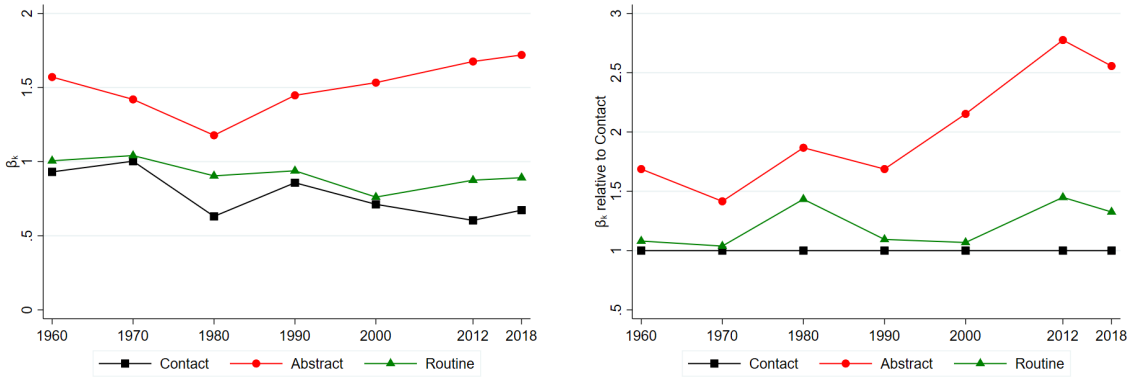
Appendix G Additional Quantitative, Empirical, and Robustness Results

In this section, we discuss additional quantitative, empirical and robustness results mentioned in the main text.

Appendix G.1 Model Estimated *Level* of β_{kt}'s

In Panel B of Figure 6 of the main text, we show the model implied *relative* β_{kt}'s. That figure highlights how the relative return to *Abstract* tasks was relatively constant between 1960 and 1980 and then increased substantively after 1980. Panel A of Appendix Figure A11 shows the *level* of model implied β_{kt}'s for the various task measures (as opposed to their *relative* values). We re-display the relative values in Panel B for completeness.

Figure A11: Task Premium Trends 1980 - 2018



Panel A: β_k's

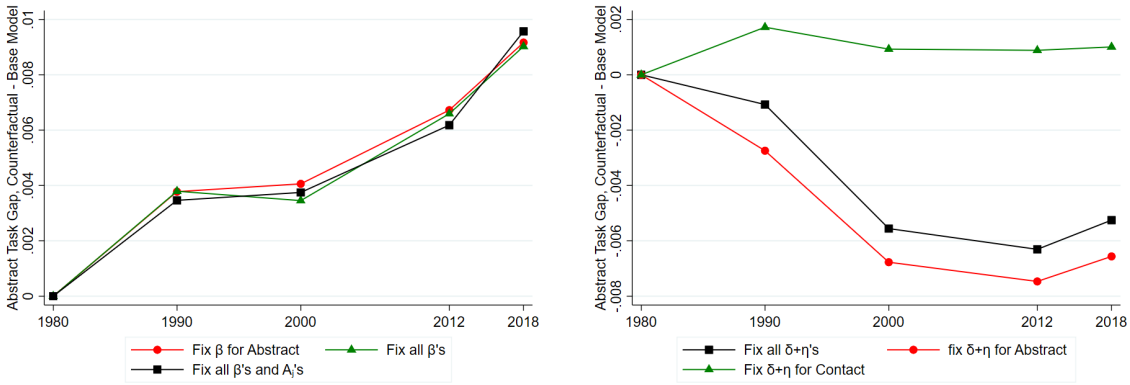
Panel B: β_k's relative to Contact

Notes: Figure shows trends in model estimated task prices, β_k's; Panel A presents the trends in β_{kt}'s as they are, while Panel B normalizes β_{kt} for *Contact* to one and shows the trends in relative values of β_{kt}'s.

Appendix G.2 The Evolution of the Abstract Task Gap Overtime

Figure A12 uses the model to estimate how the racial gap in *Abstract* tasks would have evolved if task returns were held fixed (Panel A) and if various η's and δ's were held fixed

Figure A12: Counterfactual Racial Gap in *Abstract* Tasks 1980 - 2018



Panel A: Holding Task Returns (β's) Fixed

Panel B: Holding δ's and η's Fixed

Notes: Figure shows counterfactual racial task gaps assuming various β_{kt}'s and A_{jt}'s are held fixed at 1980 levels (Panel A) and various $\delta_{kt}^{taste} + \eta_{kt}$'s are held fixed at 1980 levels (Panel B). Both figures show the percentage point change in the racial task gaps in 1990, 2000, 2012, and 2018 – relative to 1980 – from the various counterfactuals.

(Panel B) relative to the baseline trend. Like the wage gaps, the relatively constant racial gap in *Abstract* tasks over time is the result of two offsetting effects. On the one hand, the increase in *Abstract* task returns since 1980 widened the racial gap in *Abstract* tasks by drawing relatively more Whites to occupations requiring these tasks; the entry of Black men into these occupations was relatively limited as Blacks faced high barriers in *Abstract* tasks. Quantitatively, the model finds that the large increase in $\beta_{Abstract,t}$ widened the racial gap in *Abstract* tasks by about an additional 1 percentage point between 1980 and 2018 (on a baseline of about a 3 percentage point gap), relative to the counterfactual scenario where the task returns remained unchanged (Panel A). On the other hand, the model suggests that the reduction in taste-based discrimination and racial skill gaps reduced the racial gap in *Abstract* tasks by about 1 percentage point during the period relative to the counterfactual scenario where these race-specific factors were held fixed (Panel B). Overall, the effect of the improvement in race-specific factors was almost exactly offset by the effect of increasing *Abstract* task returns, and the racial gap in *Abstract* tasks remained roughly constant over the last forty years despite a narrowing of the racial barriers in *Abstract* skills ($\eta_{Abstract,t} + \delta_{Abstract,t}^{taste}$) during this period.

Appendix G.3 Pre-Labor Market Skills and Occupational Sorting, Reduced Form Estimates

In the main text, we develop a procedure that links NLSY pre-labor market traits to analogs in our model. These results rely on estimates from our structural model. In this section of the appendix we use data from the NLSY to show reduced form estimates of the mapping between an individual's pre-labor market traits and their subsequent occupational choice when they were adults. For these results, we focus on a sample of individuals between the ages of 25 and 54 pooling together respondents from both the NLSY79 and NLSY97 samples.

The results are shown in Appendix Table A4. Each column comes from a separate regression projecting an individual's cognitive, non-cognitive or social skills on the relative task content of the occupation in which an individual works. We define the relative task content of occupation o in which individual i works as $\tau_{io}^k - \bar{\tau}_{io}$ where $\bar{\tau}_{io}$ is the simple average of the *Abstract*, *Routine*, *Manual*, and *Contact* task measures for occupation o.[42] Specifically, the regression coefficients in the first column of Table 1 come the following specification:

$$S_{io,cog}^{NLSY} = \alpha + \sum_k \omega_k(\tau_{io}^k - \bar{\tau}_{io}) + \Gamma X_i + \epsilon_{io} \tag{A2}$$

where $S_{io,cog}^{NLSY}$ is the cognitive skill measure of individual i working in occupation o and X_i is a vector of individual age and education controls. Our coefficients of interest are the ω_k's. Given collinearity, we omit the relative task measure for *Manual* tasks from the regression implying that the ω_k's should be interpreted as the effect of working in an occupation that requires more of task k relative to *Manual* tasks on the cognitive skills of workers. In columns 2 and 3, we replace the dependent variable in equation (A2) with the individual's non-cognitive skills ($S_{io,ncog}^{NLSY}$) and social skills ($S_{io,soc}^{NLSY}$), respectively.

Appendix Table A4 highlights that individual pre-labor market traits differentially differentially predicts the relative task content of the occupation the individual works in when they are adults. Workers with higher AFQT scores (cognitive skills) are more likely to match with jobs that require higher *Abstract* tasks. Conversely, workers with higher social skills are more likely to match with jobs that require higher *Contact* tasks. The reduced form results in this appendix table are consistent with the findings from our structural model highlighted in Table 4 in the main text.

[42]For example, suppose individual i works in occupation o = *Civil Engineer*. As noted in the main text, the *Abstract*, *Routine*, *Manual*, and *Contact* task content for the Civil Engineering occupation are, respectively, 2.3, 1.2, 0.6, and 0.1 (in z-score units). For individuals working in Civil Engineering, $\bar{\tau}_{io}$ would equal 0.9 and the relative task demand for *Abstract* tasks in this occupation would be 1.4 (2.3 - 0.9).

Table A4: The Matching Between Individual Pre-Labor Market Traits and Relative Job Tasks Among NLSY Respondents

	Cognitive Skills	Non-Cognitive Skills	Social Skills
(1) *Abstract* Tasks	0.179	0.043	0.030
	(0.015)	(0.021)	(0.020)
(2) *Routine* Tasks	0.077	0.010	0.004
	(0.019)	(0.025)	(0.025)
(3) *Contact* Tasks	0.117	0.067	0.082
	(0.019)	(0.024)	(0.023)
Difference (1) - (3)	0.062	-0.024	-0.052
	(0.021)	(0.029)	(0.029)
Demographic Controls	Yes	Yes	Yes

Notes: Table shows the relationship between the individual pre-labor market traits and the relative task content of the individual's occupation. Each column is a separate regression. The last row shows the difference between the coefficient on relative *Abstract* tasks and relative *Contact* tasks. Robust standard errors clustered at the individual level show in parenthesis. Data uses the pooled sample of the NLSY 1979 and 1997 waves. Sample restricted to White men between the ages of 25 and 54. Individual skills and occupational task contents measured in z-score units.

Appendix G.4 The Relationship Between Log Wages and Pre-Labor Market Traits, NLSY Data

In this section of the appendix, we assess the extent to which there are racial differences in the responsiveness of wages to individual pre-labor market traits. The coefficients in Appendix TableA5 comes from a regression of log individual wages of NLSY respondents on NLSY cognitive, non-cognitive and social skill measures and those skill measures interacted with a race dummy. The regression also includes age, education and occupation fixed effects and those fixed effects interacted with a race dummy. Finally, the regression also includes year and NLSY97 sample fixed effects and those fixed effects interacted with a race dummy. For this regression, we pool together both the NLSY79 and NLSY97 samples. As with the rest of the paper, we only include in our sample Black and White men between the ages of 25 and 54.

The table highlights the labor market returns to cognitive, non-cognitive and social skills for White men (column 1). As seen from the table, having more of any of the three skill

Table A5: Racial Differences in the Relationship between Log Wages and Pre-Labor Market Traits, NLSY

	White Men	Race Gap
Cognitive	0.070	0.037
	(0.009)	(0.015)
Non-Cognitive	0.034	-0.004
	(0.007)	(0.011)
Social	0.014	0.001
	(0.007)	(0.011)

Note: Table shows key coefficients from a regression of log wages on cognitive, non-cognitive, and social skills and those skill measures interacted with a Black dummy using the NLSY micro data. The coefficients on the three pre-labor market traits are shown in column 1 and represent the log wage response for White men to a one-standard deviation increase in the pre-labor market task measures. The coefficients interacted with the Black dummy are shown in column 2 and represent the differential response log wage response between Black and White men. All regressions also include controls for individual age, education, and occupation and those controls interacted with a race dummy. Additionally, the regression also includes year and sample fixed effects plus those fixed effects interacted with a race dummy. The sample includes all Black and White men in both waves of the NLSY data between the ages of 25 and 54. Robust standard errors clustered at the individual level are shown in parentheses.

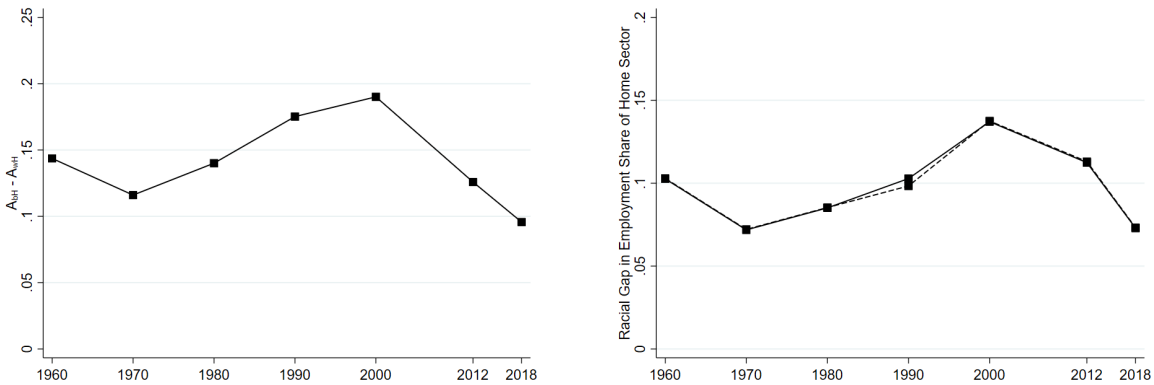
measures raises labor market earnings for White men (even conditional on individual education and occupation). Furthermore, we find no differential labor market returns for Black men for non-cognitive and social skills (column 2). However, similar to the findings in Neal (2006), the coefficient on AFQT in a regression of log wages on AFQT scores is larger for Blacks than for Whites. This is consistent with the conjecture that Black men who receive the same AFQT test score relative to White men (conditional on education and occupation) may be positively selected in traits not measured in the NLSY that are rewarded in the labor market.

Appendix G.5 Model Estimates of Home Sector Preferences

In this section, we report the model estimates of the racial gap between preferences for the home sector in each year: $A_{bHt} - A_{wHt}$. The racial gap in the A_{gH}'s ensures that the model matches labor force participation of Black and White men in each year. The results are shown in Appendix Figure A13. For the most part, Panel A shows that the racial gap in the A_{gH}'s are relatively constant over time. However, it should be noted that the model does generate a slight increase in the preference for the home sector between Black and White men

between 1980 and 2000 and a slight decline in the relative home sector preference thereafter. The relatively preferences are essentially unchanged in 1970, 1980, 2012 and 2018 relative to 1960. Panel B shows that the racial gap in non-employment rates between Black and White men both in the model (solid line) and the data (dashed line). It is not surprising that our model is matching the empirical racial gap in employment rates because we are targeting the moment. Our model estimates of $A_{bHt} - A_{wHt}$ basically just tracks the racial gap in non-employment rates between Black and White men over time.

Figure A13: Racial Differences in Home Sector Preferences



Panel A: Difference in A_{gH} Panel B: Gap in Home Sector Shares

Notes: Panel A of Figure shows the estimated differences in race-specific home sector preference parameters, A_{bH} and A_{wH}. Panel B shows the racial difference in non-employment rates in the model (solid line) and Census/ACS data (dashed line) for prime age Black and White men.

Appendix G.6 Counterfactual Robustness to Alternate θ's and ψ's

Appendix Table A6 highlights that many of our key findings are quite robust to our choice of θ and ψ. The table shows the robustness of the results of the contribution of the race-specific driving forces ($\delta_{kt}^{taste} + \eta_{kt}$ for all tasks) and the race-neutral driving forces ($\beta_{kt} + A_{ot}$ for all tasks and occupations) for alternate values of θ and ψ. In column 1, we re-report our baseline results with $\theta = 6$ and $\psi = 4.5$. In columns 2 and 3, we show the robustness of results when we set $\theta = 4$ and $\theta = 8$, respectively. As seen from the table, our key results on why the racial wage gap has stagnated post-1980 are relatively unchanged. Across the alternate values of θ and ψ, changes in race-neutral driving forces widened the racial wage gap by between 4.5 and 6.7 percentage points between 1980 and 2018. Likewise, across the alternate values of θ and ψ, changes in the race-specific driving forces reduced the racial wage gap by between 4.0 and 6.9 percentage points. We conclude that are key results are robust to alternate values of θ and ψ.

Table A6: Contribution of Various Forces to Changing Racial Wage Gaps Between 1980 and 2018, Robustness to Alternate θ's and ψ's

	Base	$\theta = 4$	$\theta = 8$	$\psi = 3.5$	$\psi = 5.5$
$\delta_{bkt}^{taste} + \eta_{bkt}$	0.065	0.054	0.069	0.040	0.066
β_{kt}'s and A_{ot}'s	-0.063	-0.051	-0.067	-0.045	-0.061

Note: Table shows the robustness of key decompositions of the racial wage gap between 1980 and 2018 to both the changes in the model's race-specific driving forces (row 1) and the changes in the model's race-neutral driving forces (row 2) across alternate values of θ and ψ.

Appendix H Proposition Proofs and Additional Estimation Details

This section of the appendix provides details on additional model results.

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 $\omega_{got}(\vec{\phi})$ and their non-pecuniary idiosyncratic preference for occupations $\log \nu_{io}$. Recall furthermore that the occupational preferences ν_{ij} follow a Frechet distribution with scale 1 and shape ψ. 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:

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

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

Appendix H.1.2 Proofs of Propositions 1-4

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

$$d \log \rho_{got}(\vec{\phi}) = \psi \left[d\omega_{got}(\vec{\phi}) - \sum_{o' \neq H} \rho_{go't}(\vec{\phi}) d\omega_{go't}(\vec{\phi}) \right].$$

Thus, the total derivative of the mean log wage $\overline{\omega}_{gt}(\vec{\phi}) = \sum_{o \neq H} \rho_{got}(\vec{\phi}) \omega_{got}(\vec{\phi})$ is given by

$$\begin{aligned}
d\overline{\omega}_{gt}(\vec{\phi}) &= \sum_{o \neq H} \rho_{got}(\vec{\phi}) d\omega_{got}(\vec{\phi}) + \sum_{o \neq H} \rho_{got}(\vec{\phi}) \omega_{got}(\vec{\phi}) d \log \rho_{got}(\vec{\phi}) \\
&= \sum_{o \neq H} \rho_{got}(\vec{\phi}) d\omega_{got}(\vec{\phi}) + \psi \left[\sum_{o \neq H} \rho_{got}(\vec{\phi}) \omega_{got}(\vec{\phi}) d\omega_{got}(\vec{\phi}) - \overline{\omega}_{gt}(\vec{\phi}) \sum_{o' \neq H} \rho_{go't}(\vec{\phi}) d\omega_{go't}(\vec{\phi}) \right] \\
&= \sum_{o \neq H} \rho_{got}(\vec{\phi}) d\omega_{got}(\vec{\phi}) + \psi \left[\sum_{o \neq H} \rho_{got}(\vec{\phi}) \left(\omega_{got}(\vec{\phi}) - \overline{\omega}_{gt}(\vec{\phi}) \right) d\omega_{got}(\vec{\phi}) \right].
\end{aligned}$$

The expression is intuitive. The first term is the direct effect of the change in 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 $\overline{\omega}_{gt}(\vec{\phi})$ 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.

Finally, the total derivative of the mean log wage in each occupation is given by

$$d\omega_{got}(\vec{\phi}) = dA_{ot} + \sum_{k} \beta_{kt} \tau_{ok} (\phi_k + \eta_{gkt} + \delta_{gkt}) \left\{ d \log \beta_{kt} + d \log \tau_{ok} + d \log(\phi_k + \eta_{gkt} + \delta_{gkt}) \right\}.$$

Substituting this expression into the total derivatives above will yield the results in Propositions 1, 2, and 4. To prove Proposition 3, note the total derivative of the average task content $\overline{\tau}_{gkt}(\vec{\phi})$ is given by

$$d\overline{\tau}_{gkt}(\vec{\phi}) = \sum_{o \neq H} \rho_{got}(\vec{\phi}) d\tau_{ok} + \psi \left[\sum_{o \neq H} \rho_{got}(\vec{\phi}) \left(\tau_{ok} - \overline{\tau}_{gkt}(\vec{\phi}) \right) d\omega_{got}(\vec{\phi}) \right],$$

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

$$d \log L_{gt}(\vec{\phi}) = \psi (1 - L_{gt}(\vec{\phi})) \left[d\omega_{got}(\vec{\phi}) - \sum_{o' \neq H} \rho_{go't}(\vec{\phi}) d\omega_{go't}(\vec{\phi}) \right].$$

Appendix H.2 Additional Comparative statics

This section presents additional comparative static results extending Section 2.6.

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 calibration to pin down the Frechet shape parameter ψ for the occupational preference distribution.

Proposition 5. *Race-neutral and race-specific forces affect the conditional labor market participation rate $L_{gt}(\vec{\phi})$ as follows:*

$$\frac{dL_{gt}(\vec{\phi})}{d\beta_{kt}} = -\psi L_{gt}(\vec{\phi})(1 - L_{gt}(\vec{\phi}))\left(\tau_{Hk} - \overline{\tau}_{gkt}(\vec{\phi})\right)(\phi_k + \eta_{gkt} + \delta_{gkt}),$$

$$\frac{dL_{gt}(\vec{\phi})}{d(\eta_{gkt} + \delta_{gkt})} = -\psi L_{gt}(\vec{\phi})(1 - L_{gt}(\vec{\phi}))\left(\tau_{Hk} - \overline{\tau}_{gkt}(\vec{\phi})\right)\beta_{kt}.$$

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 $\overline{\tau}_{gkt}(\vec{\phi})$, then a rise in the task price will induce some workers to exit the labor market if they possess skills for the task.[43]

Proposition 6. *The scale parameter for home sector preference, A_{gH}, affects the conditional labor market participation rate $L_{gt}(\vec{\phi})$ as follows:*

$$\frac{dL_{gt}(\vec{\phi})}{dA_{gH}} = -\psi L_{gt}(\vec{\phi})(1 - L_{gt}(\vec{\phi})) \leq 0.$$

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

Corollary 7. *The labor supply elasticity ε_{gt} is given by*

$$\varepsilon_{gt} \equiv -\frac{1}{\overline{L}_{gt}} \int \frac{dL_{gt}(\vec{\phi})}{dA_{gH}} dF(\vec{\phi}) = \psi \int \frac{L_{gt}(\vec{\phi})(1 - L_{gt}(\vec{\phi}))}{\overline{L}_{gt}} dF(\vec{\phi}).$$

The first equality holds because a symmetric increase in log wages of all occupations is isomorphic to a decrease in A_{gH}.

[43] See Appendix Section Appendix H.1.2 for the derivation of this proposition and the next.

Appendix H.2.2 Derivatives of Aggregate Racial Wage Gap

In the main text, we derived an approximate result for comparative statics on aggregate wages $\overline{\omega}_{gt}^{agg}$, 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 8. *Race-neutral and race-specific forces affect the aggregate wage $\overline{\omega}_{gt}^{agg}$ for workers of group g as follows:*

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

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

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 4). The second term, on the other hand, captures the extensive margin adjustment in labor market participation; increased participation rates ($d \ln L_{gt} > 0$) among workers who would on average earn a higher wage than the current aggregate wage (i.e., workers with $\overline{\omega}(\vec{\phi}) > \overline{\omega}_{gt}^{agg}$) tend to push up the aggregate wage. Naturally, the derivatives of the racial wage gap $\overline{\omega}^{gap} \equiv \overline{\omega}_{bt}^{agg} - \overline{\omega}_{wt}^{agg}$ are given by the difference of the respective derivatives for $g = b$ and $g = w$. That is, $\frac{d\overline{\omega}^{gap}}{d\beta_{kt}} = \frac{d\overline{\omega}_{bt}^{agg}}{d\beta_{kt}} - \frac{d\overline{\omega}_{wt}^{agg}}{d\beta_{kt}}$ and $\frac{d\overline{\omega}^{gap}}{d(\eta_{bkt}+\delta_{bkt})} = \frac{d\overline{\omega}_{bt}^{agg}}{d(\eta_{gkt}+\delta_{gkt})}$.

Appendix H.2.3 Miscellaneous Propositions

The exercises in Sections 4.2 and 7.3 decomposing contributions of various model forces to the evolution of the racial wage gap requires us to take the derivatives of the aggregate wage with respect to all moving parts of the model. Next three propositions give the derivatives not give in the main text but used in the quantitative exercises:

Proposition 9. *(Cross-derivative counterpart of Proposition 3) Race-neutral and race-specific forces impact the average task content $\overline{\tau}_{gkt}(\vec{\phi})$ performed by group g workers with skill draws $\vec{\phi}$ according to:*

$$\frac{d\overline{\tau}_{gkt}(\vec{\phi})}{d\beta_{k't}} = \psi \operatorname{cov}_{g,\vec{\phi}}(\tau_{ok}, \tau_{ok'})(\phi_{k'} + \eta_{gk't} + \delta_{gk't}),$$

$$\frac{d\overline{\tau}_{gkt}(\vec{\phi})}{d(\eta_{gk't} + \delta_{gk't})} = \psi \operatorname{cov}_{g,\vec{\phi}}(\tau_{ok}, \tau_{ok'})\beta'_k,$$

where $\operatorname{cov}_{g,\vec{\phi}}(\tau_{ok}, \tau_{ok'}) = \sum_o \rho_{got}(\tau_{ok} - \overline{\tau}_{gkt}(\vec{\phi}))(\tau_{ok'} - \overline{\tau}_{gk't}(\vec{\phi}))$ denotes the co-variance between the amounts of task k and task k' performed by group g workers with skill draws $\vec{\phi}$.

Proposition 10. *The derivatives with respect to occupation effects A_{ot}, $o \neq H$, are given by:*

$$\frac{d\overline{\tau}_{gkt}(\vec{\phi})}{dA_{ot}} = \psi\rho_{got}(\vec{\phi})(\tau_{ok} - \overline{\tau}_{gkt}(\vec{\phi})),$$

$$\frac{d\overline{\omega}_{gt}(\vec{\phi})}{dA_{ot}} = \rho_{got}(\vec{\phi}) + \psi\rho_{got}(\vec{\phi})(\omega_{got}(\vec{\phi}) - \overline{\omega}_{gt}(\vec{\phi})),$$

$$\frac{dL_{gt}(\vec{\phi})}{dA_{ot}} = \psi L_{gt}(\vec{\phi})(1 - L_{gt}(\vec{\phi}))\rho_{got}(\vec{\phi}) \geq 0,$$

$$\frac{d\overline{\omega}^{agg}_{gt}}{dA_{ot}} = \int \left[\frac{d\overline{\omega}_{gt}(\vec{\phi})}{dA_{ot}} + (\overline{\omega}_{gt}(\vec{\phi}) - \overline{\omega}^{agg}_{gt}) \frac{d\ln L_{gt}(\vec{\phi})}{dA_{ot}} \right] \frac{L_{gt}(\vec{\phi})}{\overline{L}_{gt}} dF(\vec{\phi}).$$

Proposition 11. *The derivatives with respect to occupation effects τ_{ok} are given by:*

$$\frac{d\overline{\tau}_{gk't}(\vec{\phi})}{d\tau_{ok}} = \begin{cases} \rho_{got}(\vec{\phi}) + \dfrac{d\overline{\tau}_{gk't}(\vec{\phi})}{dA_{ot}} \beta_{kt}(\phi_k + \eta_{gkt} + \delta_{gkt}), & k = k', \\ \dfrac{d\overline{\tau}_{gk't}(\vec{\phi})}{dA_{ot}} \beta_{kt}(\phi_k + \eta_{gkt} + \delta_{gkt}), & k \neq k', \end{cases}$$

$$\frac{d\overline{\omega}_{gt}(\vec{\phi})}{d\tau_{ok}} = \frac{d\overline{\omega}_{gt}(\vec{\phi})}{dA_{ot}} \beta_{kt}(\phi_k + \eta_{gkt} + \delta_{gkt}),$$

$$\frac{dL_{gt}(\vec{\phi})}{d\tau_{ok}} = \frac{dL_{gt}(\vec{\phi})}{dA_{ot}} \beta_{kt}(\phi_k + \eta_{gkt} + \delta_{gkt}),$$

$$\frac{d\overline{\omega}^{agg}_{gt}}{d\tau_{ok}} = \int \left[\frac{d\overline{\omega}_{gt}(\vec{\phi})}{d\tau_{ok}} + (\overline{\omega}_{gt}(\vec{\phi}) - \overline{\omega}^{agg}_{gt}) \frac{d\ln L_{gt}(\vec{\phi})}{d\tau_{ok}} \right] \frac{L_{gt}(\vec{\phi})}{\overline{L}_{gt}} dF(\vec{\phi}).$$

Refer to Section Appendix H.1.2 for the derivations.

Appendix H.3 Estimation Details

Appendix H.3.1 Construction of τ_{ok}'s for the Model Estimation

As discussed in the text, 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. 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.[44] Second, we linearly project the aggregated z-scores of task content to the unit interval [0, 1] to ensure that all task requirements we use in the model are non-negative. The two assumptions underlying these projections 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 H.3.2 Calibration of Distributional Parameters, θ and ψ

In the estimation, we assume that the skill endowment ϕ_{ik} follows a Frechet distribution with shape θ and a scale parameter of 1, both of which are constant over time and across racial groups. Likewise, the occupational preference ν_{iot} follows a Frechet distribution with shape ψ and a scale parameter of 1, both of which are constant over time and across racial groups. This section explains how we calibrate the shape parameters θ and ψ in more detail.

First, we pin down the shape θ for skill draws using the average within-occupation variation in log income. Intuitively, a smaller θ translates to a higher degree of heterogeneity in skill endowments ϕ_{ik}'s among workers in the same occupation (for given employment shares) and therefore a higher variance in log earnings within each occupation. The average of the within-occupation variance in log earnings for White men (weighted by employment shares) is about 0.27 in the 1990 Census. We recognize, however, that the measured variance is likely to reflect a significant amount of measurement error stemming from household misreporting of annual earnings or because some of cross-individual variance in earnings stems from

[44] 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 racial wage gap is virtually zero.

transitory fluctuations in income. Conversely, the model variance captures variations coming from skill differences only. In fact, for a broad range of θ values, the model variance in 1990 is stable at a little above one. As we lower θ below 6, the model variance gradually increases, but we start to miss the target for the Mincerian return to *Abstract* tasks for White men with smaller values of θ. Thus, we choose a value of $\theta = 6$. As seen in the robustness exercises above, our results are robust to alternate values of θ. This is in part because the occupation effects A_{ot}'s can adjust to match the observed patterns of sorting.

Second, we identify the shape ψ for the distribution of idiosyncratic occupational preferences using the elasticity of labor supply. There is a clear analytical relationship between the elasticity of labor supply and the heterogeneity of the occupational preferences $1/\psi$, as demonstrated in Corollary 7 in Appendix H.2. 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. Chetty et al. (2013) suggests the extensive margin elasticity of labor supply of about 0.25. We calibrate ψ using the 1990 data to fit this moment and apply the estimates to all years. Specifically, when calibrating the model for White men in 1990, we include the moment in the objective for the parameter search and search for ψ along with other parameters. We estimate a value of $\psi = 4.54$. We explore the robustness of model results to alternate values of θ and ψ in Appendix G.6.

Appendix H.3.3 Other Estimation Details

Section 4.1 of the text discusses the estimation procedure in detail. This section provides some additional details not mentioned in the text.

Optimization Algorithm The parameter search uses the interior-point method for non-linear optimization. Before starting the optimization, we draw task-specific skills for 10,000 workers. Then, for each set of parameters we evaluate in the optimization process, we calculate the employment 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 4.1. We search over the parameters to minimize the distance.

Weights in the Estimation of Race-Specific Barriers Recall that we estimate the composite race-specific term $(\delta_{bkt}^{taste} + \eta_{bkt})$ by targeting (i) the conditional racial gaps in aggregate task contents, (ii) the conditional racial gaps in task premiums, and (iii) the conditional aggregate wage gap. We minimize the weighted sum of squared deviations. Specifically, the weights on the wage gap and the task price gaps are 1/10 and 1/100 of the weights on

the task content gaps, respectively. The weight on the racial wage gap is there mainly to adjust for scaling differences; the racial wage gaps are in general about ten times larger than the task content gaps. On the other hand, we put a very small weight on the task premium gaps because the moment is not very informative; there are little trends in the moment as seen in Panel B of Figure 5. After all, Proposition 3 suggests that the task content gaps are sufficient statistics for inferring task-specific racial barriers. We nonetheless include the task price gaps among targeted moments in the optimization – with very low weights – to rule out some local minima with implausible task price gaps.

Appendix H.3.4 Decomposition of the Evolution of Racial Wage Gap

In Sections 4.2, 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_{ot}'s, β_{kt}'s, $\delta_{kt}^{taste} + \eta_{kt}$'s, and A_{gHt}'s — 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 $\vec{x}_t = (\{A_{ot}\}_o,\ \{\beta_{kt}\}_k,\ \{\delta_{kt}^{taste} + \eta_{kt}\}_k,\ \{A_{gHt}\}_g)$ 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 racila wage gap $\overline{\omega}^{gap}(\vec{x}(s)) \equiv \overline{\omega}_b^{agg}(\vec{x}(s)) - \overline{\omega}_w^{agg}(\vec{x}(s))$ at each $s \in [0, 1]$ will be governed by

$$\begin{aligned}
\frac{d\overline{\omega}^{gap}(\vec{x}(s))}{ds} = & \sum_{o \neq H} \frac{d\overline{\omega}^{gap}(\vec{x}(s))}{dA_o}\ [A_{o,1990} - A_{o,1980}] + \sum_g \frac{d\overline{\omega}^{gap}(\vec{x}(s))}{dA_{gH}}\ [A_{wH,1990} - A_{wH,1980}] \\
& + \sum_k \frac{d\overline{\omega}^{gap}(\vec{x}(s))}{d\beta_k}\ [\beta_{k,1990} - \beta_{k,1980}] \\
& + \sum_k \frac{d\overline{\omega}^{gap}(\vec{x}(s))}{d(\delta_{bk} + \eta_{bk})}\ [(\delta_{bk,1990} + \eta_{bk,1990}) - (\delta_{bk,1980} + \eta_{bk,1980})] \\
& + \frac{d\overline{\omega}^{gap}(\vec{x}(s))}{dA_{bH}}\ [(A_{bH,1990} - A_{wH,1990}) - (A_{bH,1980} - A_{wH,1980})]\,,
\end{aligned}$$

where the derivatives are derived in Sections 2.6 and Appendix H.2 above.[45] At each $s \in [0, 1]$, the first two lines on the right-hand side capture the marginal contributions of race-neutral effects; the third line captures the marginal contributions of changing task-specific racial

[45] In addition to these model driving forces, the task requirements τ_{kt}'s in the model vary slightly over time due to aggregation by year (see Appendix H.3.1). In the quantitative exercise, we take this into account by including τ_{kt}'s in the vector $\vec{x}$ of model variables – this introduces one additional set of terms in the time derivative of $d\overline{\omega}^{gap}$ – and report the effect of the slightly changing τ's as part of the contribution of the race-neutral forces. However, this is quantitatively inconsequential.

barriers; and the last line captures the marginal contributions of the racial difference in home sector preference. 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 racial barrier $\delta_{bkt} + \eta_{bkt}$ 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.

A caution must be taken when interpreting the contributions of task price β_{kt} for each k calculated this way. While we do not explicitly model the interdependence between task prices (β_{kt}'s) and occupational returns (A_{ot}'s) — we allow for any form of interdependence between the two in the estimation — part of the estimated changes in A_{ot}'s are likely to be induced by changes in β_{kt}'s. For example, one might imagine that a technology improvement that raises the productivity of task k across all occupations – which pushes up β_{kt} – will expand the supplies of task k-intensive goods, lower their output price, and hence depress the occupational returns A_{ot} in occupations producing these goods.[46] In fact, in our estimated model, the relative changes in A_{ot}'s over time are negatively correlated with changes in $\beta_{kt}\tau_{ok}$, i.e., when a task price for task k rises, the occupational returns are likely to fall more in occupations using task k more intensively. Since we cannot determine how much of the changes in A_{ot}'s are driven by changes in each β_{kt}, we do not attempt to calculate the separate contributions of β_{kt} for each task k. Instead, we report the combined contribution of all race-neutral forces, β_{kt}'s and A_{ot}'s.

Finally, in Section 7.3, we extend this exercise by decomposing the total contribution of the composite race-barrier (the $\delta_{bkt}^{taste} + \eta_{bkt}$) over each period into respective contributions of δ_{bkt}^{taste} and η_{bkt}. We do so based on how much of the total change in $\delta_{bkt}^{taste} + \eta_{bkt}$ over the 1960-1990 period and over the 1990-2012 period comes from a change in δ_{bkt}^{taste} versus a change in η_{bkt}. For example, of the total contribution of $\delta_{bkt}^{taste} + \eta_{bkt}$ for task k over the 1960-1970, 1970-1980, and 1980-1990 periods, we attribute the fraction

$$\frac{\delta_{bk,1990} - \delta_{bk,1960}}{(\delta_{bk,1990} + \eta_{bk,1990}) - (\delta_{bk,1960} + \eta_{bk,1960})}$$

to the changing taste-based discrimination δ^{taste}, and the remaining fraction to the changing

[46] Recall that A_{ot} is the log wage that workers with zero skills would receive in occupation o, which in a competitive labor market will equal the value marginal product of the worker.

racial skill gap η_{bkt}. Said differently, we linearly interpolate assuming that the relative speed of the decline in δ_{bkt}^{taste} versus η_{bkt} is the same across all periods between 1960 and 1990. We perform the decomposition similarly for the 1990-2000, 2000-2012, and 2012-2018 periods based on the estimated relative trends in δ_{bkt}^{taste} versus η_{bkt} over the 1990-2012 period.[47] We then compute the cumulative contributions over the 1960-1980 and 1980-2018 periods.

[47]Note that the decomposition for 2012-2018 involves a linear *extrapolation* of the estimated relative changes in δ_{bkt}^{taste} versus η_{bkt} over the 1990-2012 period.