Task-Based Discrimination

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Abstract

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

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1 Introduction

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

2 A Theory of Task Based Discrimination and Occupational Sorting

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

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

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

2.1 Occupations

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

2.2 Worker Heterogeneity

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

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

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

Task-Specific Skills All workers perform tasks by allocating a unit of labor to the occupation of their choice, but workers differ in their efficiencies at performing each type of tasks, which are drawn from a known distribution. Omitting time subscripts, we denote the skill-endowment of worker i belonging to group g with a vector $\overrightarrow{\phi^g_{ik}} = \{\phi^g_{i1}, ..., \phi^g_{iK}\} \in \mathcal{R}^K_+$, where ϕ^g_{ik} 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 $\overrightarrow{\phi^w_{ik}} = \{\phi_{i1}, ..., \phi_{iK}\}$, where each ϕ_{ik} is drawn from a Frechet distribution with shape parameter θ_k and scale parameter 1, both of which are constant over time. For Black men (g=b), we assume the vector of skill draws can be expressed as $\overrightarrow{\phi^b_{ik}} = \{\eta^b_1 + \phi_{i1}, ..., \eta^b_K + \phi_{iK}\}$, where η^b_k measures the gap in average task-specific skills between Black and White men. In short, the skill distribution for Black men in each task k is shifted by η^b_k 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^b_k's proxy for the fact that current and past discrimination can result in different groups having different levels of task-specific human capital at a given point in time.

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

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

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

of occupational sorting observed in the data.

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

2.3 Worker Wages

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

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

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

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

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

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

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

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

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

2.4 Worker Utility

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

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

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

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

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

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

2.5 Home Sector

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

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

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

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

2.6 Occupational Choice

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

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

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

Recall that idiosyncratic occupational preferences ν_{io} follow a Frechet distribution with shape parameter ψ. This implies convenient closed-form expressions for occupational shares. As derived in Appendix H, the fraction of group g workers who choose occupation o conditional on working and having skill draws $\vec{\phi} = \{\phi_1, ..., \phi_K\}$ is given by:

Table 1: Summary of Race-Specific Barriers

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

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

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

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

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

2.7 Comparative Statics and Model Implications

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

There are two takeaways from this expression. First, a reduction in race-specific barriers ($d(A_t^b) > 0$ and $d(\eta_{kt}^b + \delta_{kt}^b) > 0$) 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 ($\eta_{kt}^b < 0$), or if they are paid as if they had lower skills due to pecuniary discrimination ($\delta_{kt}^b < 0$). The second term shows that differential sorting further amplifies this effect. As highlighted by Proposition 1, the existence of pecuniary and non-pecuniary racial task barriers (η_{kt}^b, δ_{kt}^b and γ_{kt}^b) makes Black workers sort away from occupations that are intensive in the task. If skilled Black workers on average perform less of the task than comparable Whites due to high barriers – that is, if $\overline{\tau}_{kt}^b(\bar{\phi}) - \overline{\tau}_{kt}^w(\bar{\phi}) < 0$ – then they capture even less of the gains from rising task returns. In sum, the corollary implies that, given the existence of the task-specific racial barriers (η_{kt}^b, δ_{kt}^b and γ_{kt}^b), changes in race-neutral task returns (β_{kt}'s) will cause changes in the racial wage gap. Below, we will highlight this implication both through the lens of our estimated model and through model-guided empirical specifications using micro-level data.

3 Racial Differences in Occupational Tasks

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

3.1 Measuring the Task Content of Occupations

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

3.2 Measuring Occupational Sorting and Wages

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

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

3.3 Trends in Racial "Task Gaps"

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

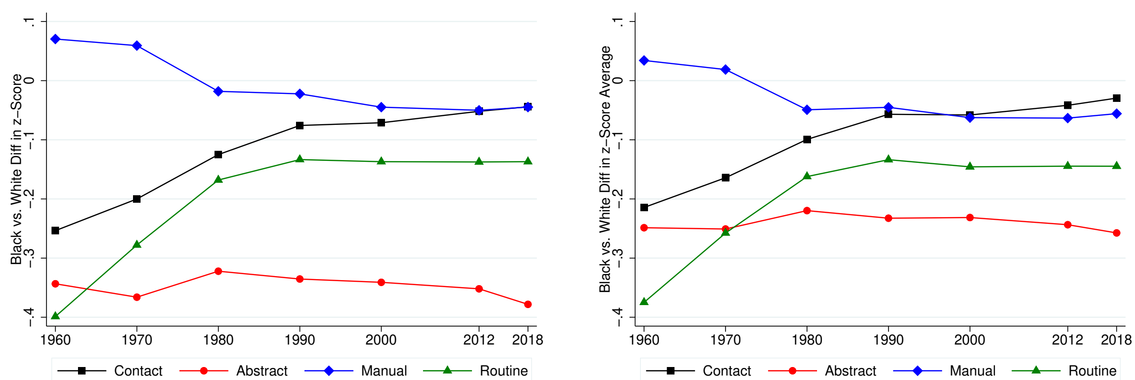
$$\tau_{o(i,t)k} = \alpha_t^k + \lambda_t^k Black_{it} + \sum_{s \neq k} \zeta_{st}^k \tau_{o(i,t)s} + \Gamma_t^k X_{it} + \epsilon_{ikt}, \tag{8}$$

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

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

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

Figure 1: Racial Differences in the Task Content of Occupations



Panel A:
No Controls

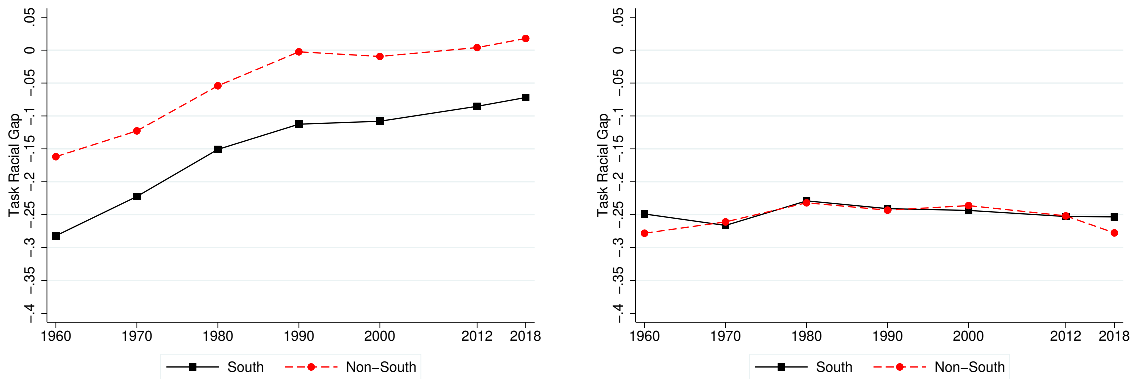
Panel B:
With Controls

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

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

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

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



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

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

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

3.4 Trends in Racial "Task Gaps" By Region

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

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

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

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

3.5 Time Series Changes in Task Returns

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

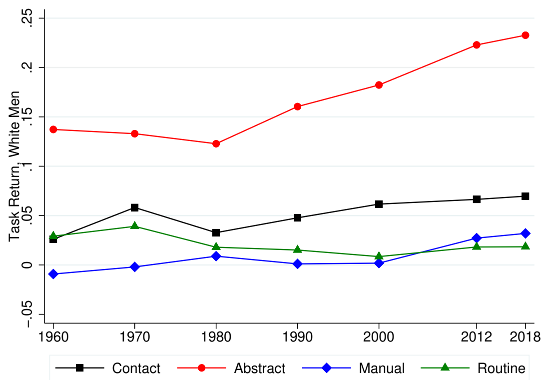
$$\omega_{iot} = \alpha_t^g + \sum_k \tilde{\beta}_{kt}^g \tau_{o(i,t)k} + \Gamma_{kt} X_{it} + \epsilon_{iot}. \tag{9}$$

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

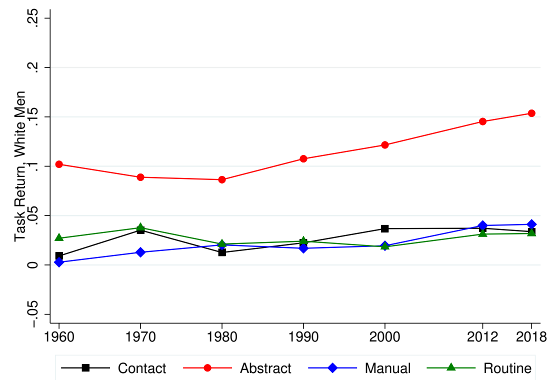
Figure 3 reports estimates of the raw wage premium by task requirement for White men (Panel A), the demographically-adjusted wage premium by task requirement for White men (Panel B) and the demographically-adjusted Black-White gaps in the wage premium by task requirement (Panel C). Three main findings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

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

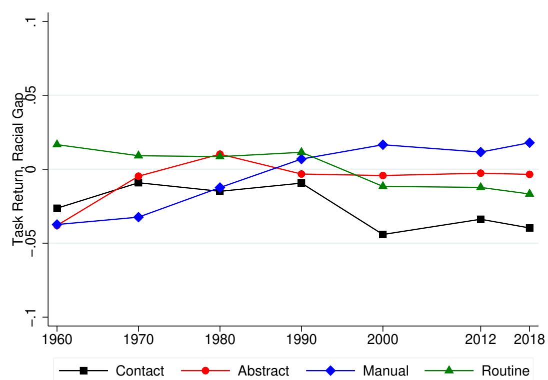
Figure 3: Mincerian Task Premiums, White Men and Racial Gap



Panel A: White Men
No Controls



Panel B: White Men
With Controls



Panel C: Racial Gap
With Controls

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

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

3.6 Racial Gap in Wages and Employment Rates

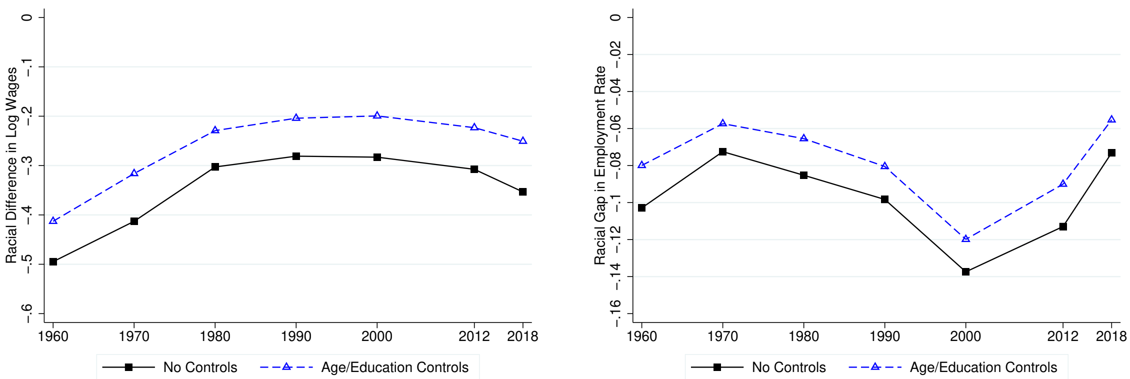
Panel A of Figure 4 shows the mean difference in log wages between Black and White men over the 1960 to 2018 period using data from the U.S. Censuses and the American Community Surveys both with (dashed line) and without (solid line) controlling for age and education. The Black-White wage gap narrowed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

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

3.7 Robustness of Racial Gap in Task Trends

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

Figure 4: Racial Wage and Employment Gaps Over Time



Panel A: Racial Wage Gap

Panel B: Racial Gap in Employment Rates

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

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

4 Model Estimation

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

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

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

We estimate the parameter vector $\Theta^w = (\{A_t\}, \{A_o\}, \{A_{Ht}\}, \{\beta_{kt}\}, \theta)$ through minimum distance estimation. The set of moments we target are: (i) the average log income of White men in each occupation in each year; (ii) log of employment share of White men in each occupation in each year; (iii) log of the non-employment rate of White men in each year; (iv) the empirical price of each task for White men in each year (shown in Figure 3 Panel A); and (v) the aggregate content of each task for White men in each year.[24] Let $\hat{m}^w$ denote the vector of moments in the data, and let $m^w(\Theta^w)$ denote the corresponding moments calculated in the model given parameters Θ_w. Our estimator $\hat{\Theta}^w$ solves

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

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

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

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

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

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

As suggested earlier, we set the shape parameter ψ externally to roughly match the empirical estimates of labor supply elasticity. As we show in Online Appendix F, the parameter ψ is closely tied to the elasticity of labor supply in the model. Intuitively, a smaller ψ translates to stronger occupational preferences (which means workers are less responsive to a change in wages) and hence a lower elasticity of labor supply. We thus set $\psi = 4.5$ as our baseline to roughly match the extensive margin labor supply elasticity of 0.5, which is within the range of labor supply elasticity estimated in the literature (Chetty et al. (2013)). We show the robustness of our results to alternate values of ψ in Appendix F.

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

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

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

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

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

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

Our estimation in the second step is equivalent to the following sequential procedure. First, we estimate the composite task-specific racial barriers $\delta_{kt}^b + \eta_{kt}^b + \gamma_{kt}^b$ and the racial gap in home sector returns A_{Ht}^b jointly from the observed racial gaps in aggregate task contents and home sector shares. Next, we parse out the pecuniary and non-pecuniary components of task-specific barriers — i.e., $\delta_{kt}^b + \eta_{kt}^b$ versus γ_{kt}^b — based on the observed racial gaps in Mincerian task premiums, noting that non-pecuniary discrimination γ_{kt}^b does not impact labor market returns except through sorting. Last, we attribute any residual aggregate wage gap unexplained by $\delta_{kt}^b + \eta_{kt}^b$, γ_{kt}^b, and A_{Ht}^b to the general non-task-related racial wedge A_t^b.

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

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

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

5 Explaining Racial Differences in Occupational Sorting and Wages

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

5.1 Estimates of Model Driving Forces

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

5.1.1 Estimates of Race-Neutral Task Returns

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

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

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

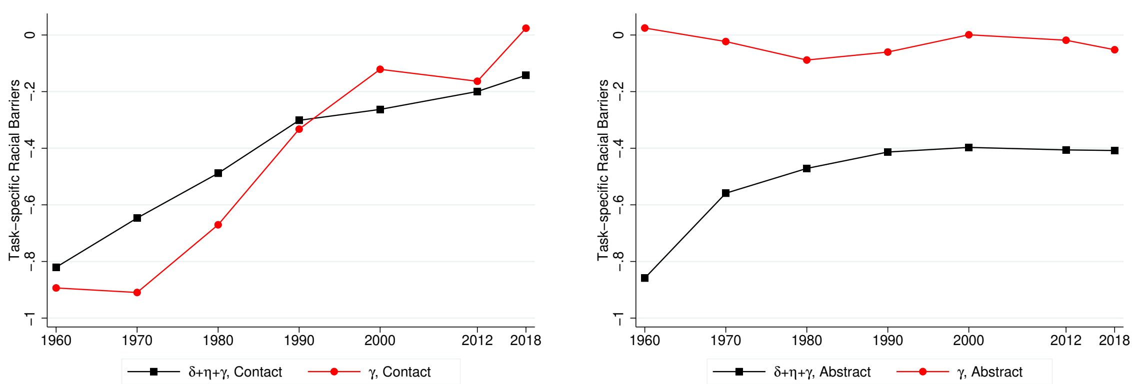
The black lines (with squares) in Panels A and B of Figure 5 show the model estimates of $(\eta^b_{kt} + \delta^b_{kt} + \gamma^b_{kt})$ for *Contact* and *Abstract* tasks, respectively. The figure shows a reduction in the composite term $(\eta^b_{kt} + \delta^b_{kt} + \gamma^b_{kt})$ for both tasks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

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

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

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

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



PANEL A: CONTACT

PANEL B: ABSTRACT

Notes: Figure shows our model estimates of the composite racial barrier $(\eta_{kt}^b + \delta_{kt}^b + \gamma_{kt}^b)$ and the component that is due to non-pecuniary discrimination (γ_{kt}^b) for *Contact* tasks (Panel A) and *Abstract* tasks (Panel B).

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

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

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

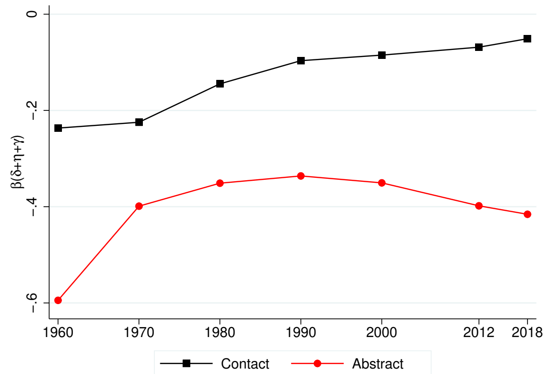
It may initially appear surprising that we find such contrasting trends for pecuniary racial barriers across the two tasks, given that the racial gaps in Mincerian task premiums in the data (shown in Figure 3) are small throughout for both tasks; the reason lies in selection on skills. One implication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

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

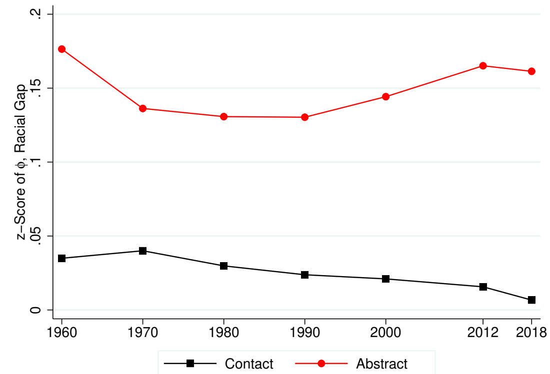
[27] The estimated racial barriers for *Routine* tasks are shown in Table 2. The composite racial barrier for *Routine* tasks narrowed from 1960 to 1980 and then remained constant thereafter. In recent years, both $(\eta^b_{kt}+\delta^b_{kt})$ and γ^b_{kt} were important in explaining the composite racial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

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

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



PANEL A: $\beta_{kt}(\eta^b_{kt} + \delta^b_{kt} + \gamma^b_{kt})$



PANEL B: $\bar{\phi}^b_{kt} - \bar{\phi}^w_{kt}$

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

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

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

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

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

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

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

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

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

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

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

5.2 Explaining Trends in the Racial Wage Gap

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

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

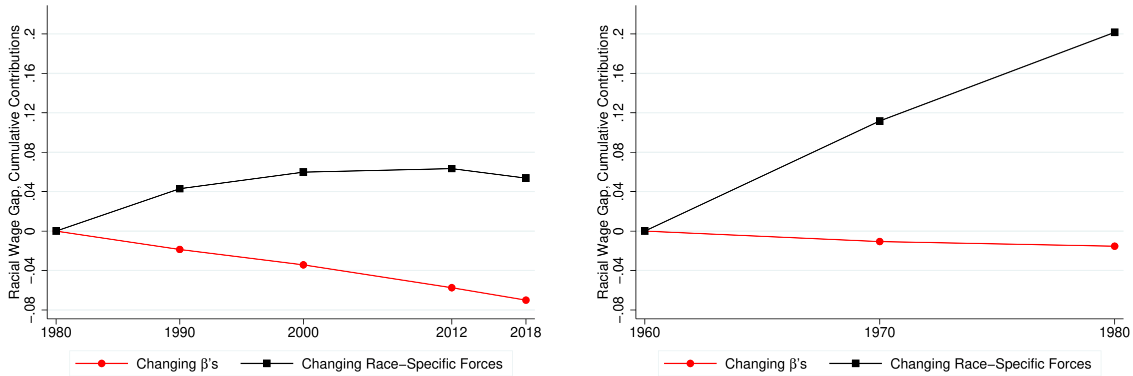
Corollary 1 in Section 2.7 illustrates the two channels through which the rising *Abstract* task return post-1980 widened the racial wage gap. First, since the racial task barriers in *Abstract* tasks had deterred many Black workers from entering occupations with high *Abstract* task requirements in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

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

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

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

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



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

Notes: Figure shows cumulative contributions of race-neutral forces (β_{kt}'s) and race-specific forces (δ_{kt}^b's, η_{kt}^b's, γ_{kt}^b's, and A_t^b's) to the evolution of the racial wage gaps over the 1980 to 2018 period (Panel A) and over the 1960 to 1980 period (Panel B).

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

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

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

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

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

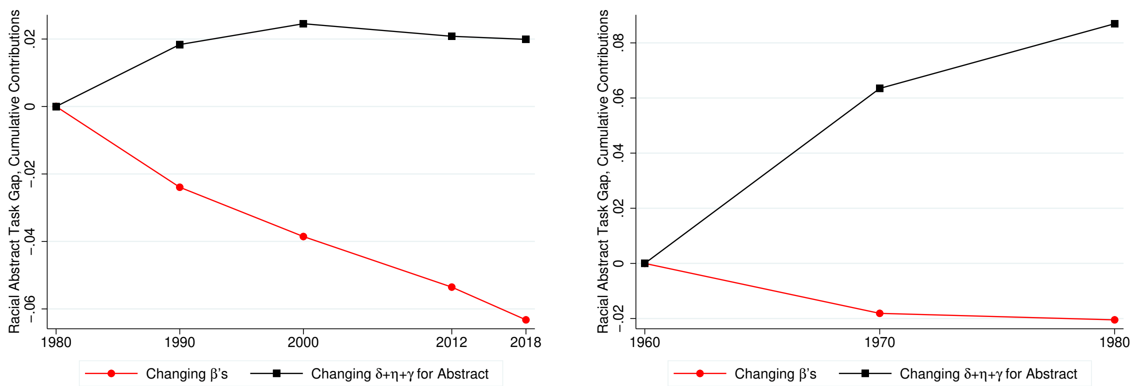
Figure 8 highlights the respective importance of the race-neutral and race-specific forces over the 1980-2018 period (Panel A) and the 1960-1980 period (Panel B) by performing the same decomposition exercise as above with the racial gap in *Abstract* tasks. Panel A shows that increasing *Abstract* task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

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

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

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

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



PANEL A: 1980-2018 PANEL B: 1960-1980

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

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

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

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

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

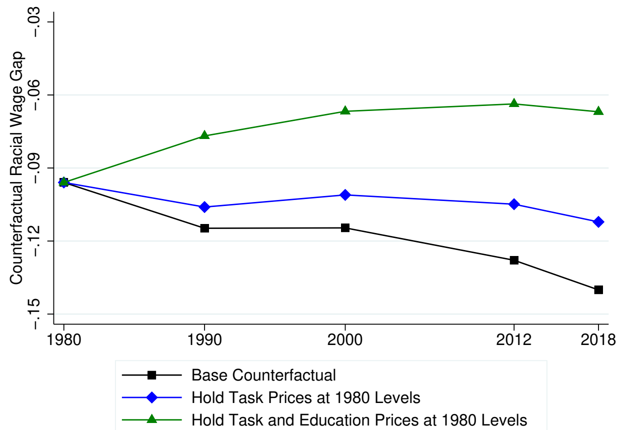
As above, the variable ω^w_{iot} is the log wage of White man i working in occupation o in time t while $\tau_{o(i,t)k}$ is the task content of occupation o in which individual i works during year t. Finally, D^E_{it} is a vector of the same five education dummies representing the education level of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

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

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

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

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



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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

7.1 Model Estimates for the South and non-South Regions

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

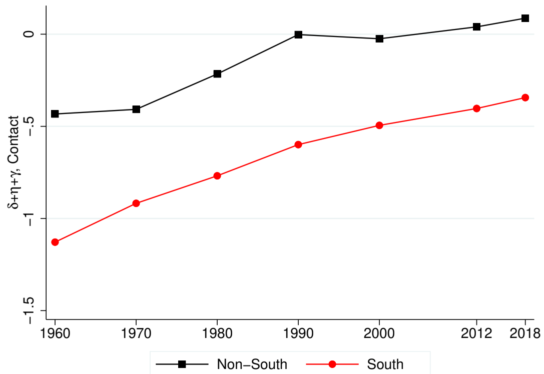
If the racial gap in *Contact* tasks is indeed a good measure of direct discrimination, we expect the composite racial barrier we estimate in the model to satisfy the following three properties in line with the survey-based measures of direct discrimination. First, the estimated composite racial barrier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

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

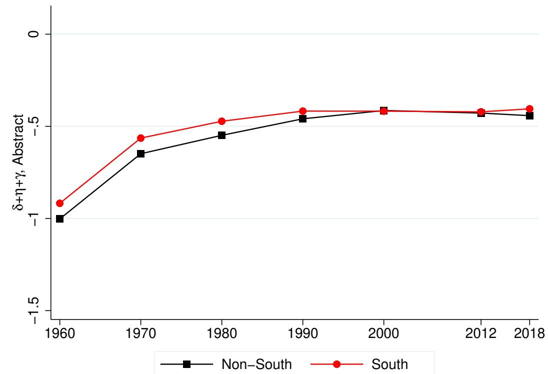
As a point of contrast, Panel B of the figure also shows the estimated composite racial

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

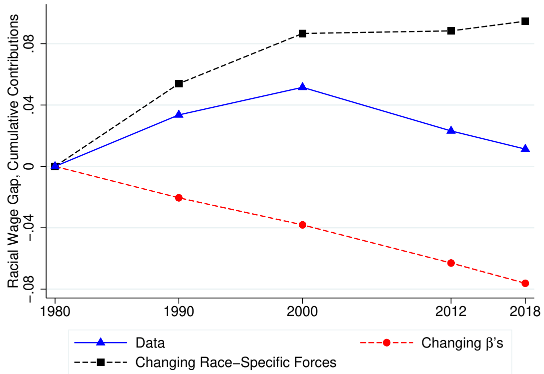
Figure 10: Racial Barriers and their Contributions to Racial Wage Gap, South vs Non-South



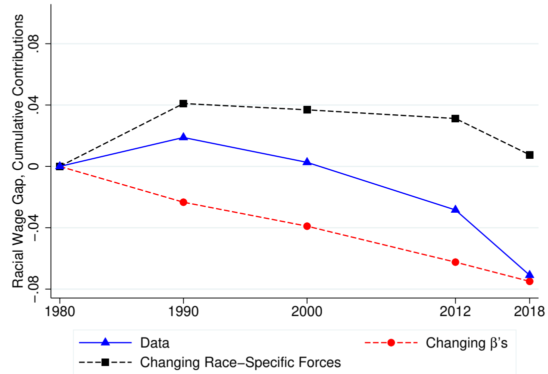
Panel A: $\eta^b_{kt} + \delta^b_{kt} + \gamma^b_{kt}$, Contact



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



Panel C: Contributions, South



Panel D: Contributions, Non-South

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

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

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

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

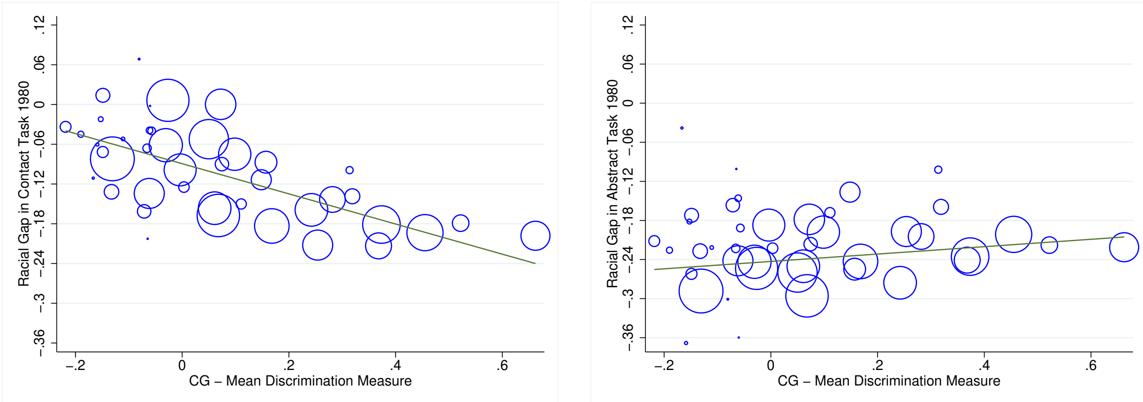
7.2 Racial Gap in *Contact* Tasks and Survey Measures of Direct Discrimination, Cross-State Variation

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

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

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

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



Panel A: Contact Tasks

Panel B: Abstract Tasks

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

levels of direct discrimination among Whites within the state.

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

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

8 Additional Results

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

To measure the extent to which Black and White men systematically differ in the skills needed to perform *Contact* and *Abstract* tasks, we use the detailed measures of pre-labor market traits from the NLSY data. Specifically, we use pre-labor market measures of performance on cognitive tests and psychometric assessments for NLSY respondents to generate a set of unified proxies for cognitive, non-cognitive and social traits across the two NLSY waves.

We take our definitions of these NLSY pre-labor market measures directly from the existing literature. First, we follow the literature and use the respondent's scores on the Armed Forces Qualifying Test (AFQT) as our measure of cognitive skills. The AFQT is a standardized test which is designed to measure an individual's math, verbal, and analytical aptitude. Second, we use measures of the Rotter Locus of Control Scale and the Rosenberg Self-Esteem Scale (for the 1979 cohort) and respondent self-reports of their conscientiousness (for the 1997 cohort) to create our non-cognitive skill measures. Finally, for the 1979 cohort, we use self-reported measures of sociability in childhood and sociability in adulthood to create a measure of social skills. For the 1997 cohort, we proxy for social skills using the two questions that were asked to capture the extroversion factor from the commonly-used Big 5 personality inventory. In particular, all of our skill measures and definitions are exactly the same as the skill measures used in Deming (2017b).

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

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

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

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

9 Conclusion

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

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

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

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

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

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