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Equilibrium Unemployment: The Role of Discrimination.*

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Abstract

U.S. labor markets are increasingly diverse and persistently unequal between genders, races and ethnicities, skill levels, and age groups. We use a structural model to decompose the observed differences in labor market outcomes across demographic groups in terms of underlying wedges in fundamentals. Of particular interest is the potential role of discrimination, either taste-based or statistical. Our model is a version of the Diamond-Mortensen-Pissarides model extended to include a life cycle, learning by doing, a nonparticipation state, and informational frictions. The model exhibits group-specific wedges in initial human capital, returns to experience, matching efficiencies, and job separation rates. We use the model to reverse engineer group-specific wedges that we then feed back into the model to assess the fraction of various disparities they account for. Applying this methodology to 1998–2018 U.S. data, we show that differences in initial human capital, returns to experience, and job separation rates account for most of the demographic disparities; wedges in matching efficiencies play a secondary role. Our results suggest a minor aggregate impact of taste-based discrimination in hiring and an important role for statistical discrimination affecting particularly female groups and Black males. Our approach is macro, structural, unified, and comprehensive.
Keywords: *Search; Unemployment; Discrimination; Statistical Discrimination; Taste-Based Discrimination; Structural; Decomposition.*
JEL Classification: *E2; J6; J7.*

1 Introduction

The U.S. population has grown increasingly diverse during the past 40 years, and it is expected to become even more diverse during the next 40 years (Figure 1). At the same time, there are significant and persistent differences in labor market outcomes between genders, races, and ethnicities that constitute an important dimension of economic inequality (Altonji & Blank, 1999; Guryan & Charles, 2012; Lang & Lehmann, 2012; Blau & Kahn, 2017; Cajner et al., 2017). Figure 2 uses data from the Current Population Survey (IPUMS, 2018) for the years 1998 to 2018 to illustrate some of these disparities over the life cycle. The figure includes eight demographic groups and four labor market outcomes: wages, unemployment, nonparticipation, and job-finding rates.[1] Given that the population shares of demographic groups with historically weaker labor market outcomes are predicted to increase in the future, the overall labor market outcomes could be weakened unless the labor market disparities are reduced.

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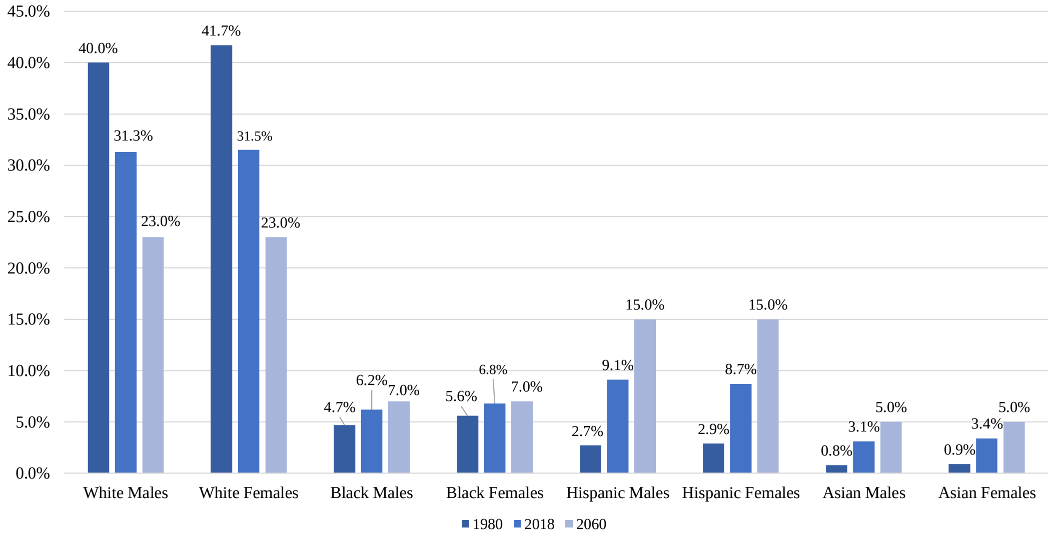
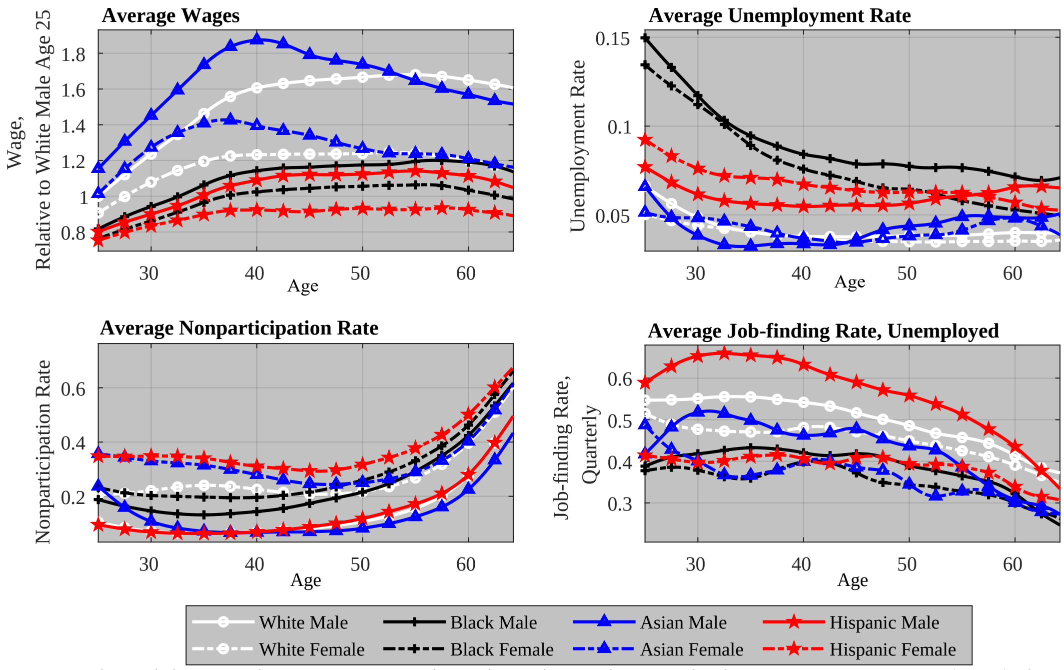
[1]See Section 3 for details.



Source: U.S. Census Bureau, 2019; U.S. Census Bureau, 2017; National Center for Health Statistics, 2021

Figure 1: Composition of the U.S. population of ages 25 to 65: 1980–2060.



Notes: These labor market statistics are based on the authors' calculations using IPUMS (2018) data for the years 1998 to 2018.

Figure 2: Selected labor markets statistics over the life cycle for different demographic groups.

What are the underlying sources of the observed labor market disparities between demographic groups? To what extent could these differences reflect discrimination? The main task of this paper is to disentangle the extent to which differences in human capital versus search frictions, which could include discrimination, account for the observed differences in labor market outcomes between different demographic groups. To measure the differences in human capital and search frictions, we use an extended version of the Diamond-Mortensen-Pissarides (DMP) search and matching model to solve for and calibrate the human capital and matching efficiency trajectories for each group. A search and matching model is a natural choice for our exercise, as it can jointly explain differences in both employment and wage outcomes—the variables of our interest—in terms of underlying economic incentives and a costly matching process.[2] We include all the major demographic dimensions in the U.S. labor market in our analysis to create a clear picture of the determinants of the aggregate labor market gaps. These dimensions include gender (females and males), race and ethnicity (Asians, Blacks, Hispanics, and Whites), age (25–65-year-olds), and skill level (skilled and unskilled).

The DMP model offers a unified general equilibrium framework in explaining aggregate labor market gaps. In the model, employers put more resources and effort into hiring workers with higher expected payoffs, higher chances of a successful search, and lower chances of a match break; each of these elements is captured by either group-specific human capital or search frictions. We further extend the standard DMP framework along the following lines to better match the observed labor market data. First, we allow workers to be nonparticipating in addition to being employed or unemployed. This feature allows us to account for the significant differences in participation rates between different genders and races. Second, we introduce life-cycle aspects to the model by assuming that workers retire deterministically at age 65, which means that the match between a retiring worker and a firm breaks at a finite time. This feature lets us study the labor market outcomes over the life cycle and life-cycle patterns of potential discrimination. Third, we allow for human capital accumulation through learning by doing. Employed workers gain experience that enhances their human capital. Being non-employed—either unemployed or a nonparticipant—is costly since experience and human capital accumulation halts. This is an important channel to consider because labor market attachment varies significantly between demographic groups. The groups that are more likely to move out of the labor force are affected through lost human capital causing stagnation in their wage growth. Firms also care about the labor market attachment of their workers: as posting a vacancy is costly for a firm, the higher likelihood of a match break has a negative effect on the number of vacancies a firm is willing to open, and the wages the firm is willing to pay. Variation in match break probabilities between groups creates an incentive for firms to engage in statistical discrimination based on the group-specific job destruction rates.

[2] Although the DMP model has been questioned in its ability to account for unemployment fluctuations (for example, by Shimer, 2005) the model remains the standard for studying the natural rate of unemployment. Our analysis can be regarded as an exploration of the determinants of unequal natural rates of unemployment among demographic groups.

We also study the potential role of discrimination in explaining the aggregate labor market disparities relying on the two main theories of discrimination, taste-based discrimination (as in Becker, 1957) and statistical discrimination (as in Arrow & Pascal, 1972 and Phelps, 1972).[3] We focus on potential discrimination in hiring and wage negotiation[4], and discrimination can be present in at least two components of the model. First, taste-based discrimination (or prejudice, which we use interchangeably with taste-based discrimination) in hiring can take the form of a wedge across groups in their matching efficiencies. In the model, variation in matching efficiencies between demographic groups is not based on variation in match values between the groups, but rather captures a residual difference in job-finding probabilities that cannot be explained by the number of vacancies and job seekers.[5] Any wedges in matching efficiencies can thus reflect prejudice of employers towards certain groups. For that reason, we measure the potential aggregate role of taste-based discrimination in describing aggregate labor market disparities by using the unexplained wedges in matching efficiencies. Second, statistical discrimination in hiring and wage bargaining can occur if firms utilize group-specific statistics to gauge the long-term prospects of a potential hire. We introduce a parametric formulation into the DMP model to control the degree to which statistical discrimination can occur. A single parameter $\mu \in [0, 1]$ determines the degree to which individuals observe group-specific statistics ($\mu = 1$) or just statistics common among groups ($\mu = 0$). The strategy to identify μ is a novel contribution of the paper. We identify the potential role of statistical discrimination in explaining labor market gaps by running a counterfactual exercise that prevents firms from using group-specific statistics when making hiring decisions.

The core of the paper is the calibration of the fundamental model parameters for each demographic group and the counterfactual exercises assessing the role of different wedges in these fundamentals in accounting for the aggregate labor market disparities. The spirit of the quantitative exercise is to let the data speak by itself through the lens of the DMP model. As in Chari, Kehoe, and McGrattan (2007)[6], we use macro accounting techniques and reverse engineer the underlying parameters—in particular, the implied parametric

[3]Taste-based discrimination (or prejudice) theory is commonly used to characterize the type of discrimination that is based on less favorable attitudes and prejudice of either employer, co-workers, or customers towards workers belonging to a certain, nonpreferred group (e.g., gender, ethnicity, race, religion, etc.). For example, a situation where an employer prefers to hire a less-qualified candidate of the preferred group over a more-qualified worker of the nonpreferred group is considered taste-based discrimination. In such a case, an employer is willing to accept a financial penalty to avoid interaction with nonpreferred workers, either because of the employer's own prejudice or that of co-workers or customers. In contrast, statistical discrimination theory is based on the idea that employers have limited information about a worker's true productivity. This can lead employers to rely on accurate or inaccurate stereotypes about a group (e.g., gender, race, ethnicity, age, etc.) the worker belongs to when making hiring decisions. For example, an employer may assess that a female job applicant is less attached to the labor force and more likely to leave a job given that female workers, on average, have a higher likelihood to leave the labor force.

[4]Other potential outcomes in the labor market can be affected by discrimination. For example, long-term wage outcomes will depend on the likelihood of getting promotions, and it is possible that some demographic groups are discriminated against in promotions.

[5]Compare to the Solow residual in growth accounting literature.

[6]Chari, Kehoe, and McGrattan (2007) use the standard growth model as their prototype model, extend it to include four time-varying wedges, and calibrate them to match the series of output, labor, consumption, and investment. They find that efficiency and labor wedges accounted for most of the postwar business cycles, while investment wedges played only a minor role.

wedges—needed to *exactly* match several targets for the studied demographic groups during the 1998–2018 period. Specifically, given estimated job separation rates and transition flows between unemployment and nonparticipation, we use the model to calculate group-specific initial levels of human capital, age-specific returns to experience, and matching efficiencies for the unemployed and the nonparticipants required to exactly match stylized life-cycle patterns of wages and job-finding rates.

The extent to which each wedge accounts for observed disparities in wages, employment, lifetime earnings, job-finding rates, and other labor market outcomes is then assessed through counterfactual exercises of closing one wedge at a time. Wedges in initial human capital and returns to experience refer explicitly to differences in the human capital of the worker and can be regarded as wedges in "fundamentals." Wedges in matching efficiencies as well as in job separation rates are "search frictions" and may include elements of taste-based and statistical discrimination.[7] Results from an accounting technique of this type are helpful to identify the most and least promising lines of future research by suggesting dimensions along which the model would need to be extended.

The following are the main results of the paper. First, our calibrated human capital series differ significantly between demographic groups.[8] However, we find that human capital differences alone cannot explain differences in the key labor market outcomes. Additional wedges in search frictions—specifically, in matching efficiencies and job destruction rates—are required for the model to be able to match the differential wage, employment, and lifetime earnings outcomes. According to the calibrated model, human capital differences account for around 65 percent of the average gap in lifetime earnings, including all groups, while search frictions account for around 32 percent. When we break down the impact of search frictions to the parts potentially coming from taste-based and statistical discrimination, respectively, we find a quantitatively small potential role for taste-based discrimination and a large role for statistical discrimination. We find that around 24 percent of the average lifetime earnings gap is accounted for by statistical discrimination, while taste-based discrimination can explain up to 3 percent of the aggregate gap. We find that there are significant differences in matching efficiencies between different demographic groups. However, as Hispanics have relatively high matching productivities compared to Whites while the matching productivities of Asian and Black women are relatively low, those wedges largely cancel out, and the matching efficiencies cannot explain a large part of aggregate gaps in the labor market outcomes.

These findings emphasize that it is important to account for search frictions when try-

[7]There exist other factors that can generate wedges in matching efficiencies. Demographic groups can simply differ in their average search effort, for example, in the number of applications they send while searching for a job. Differences in geographic locations (e.g., urban vs. rural) can drive differences in matching efficiencies if certain demographic groups are more likely to live in certain geographic locations and geographic locations vary in their matching efficiencies. Also, some occupations are subject to regulations like occupational licensing, which may impact the matching efficiency. To the extent that some demographic groups are more likely to work in occupations subject to regulations that impact hiring, regulations may also create matching efficiency gaps between demographic groups.

[8]Our estimates are roughly consistent with existing estimates in the literature, particularly with Oaxaca-Blinder decompositions (see Blau & Kahn, 2017 for a literature review for the case of gender gaps).

ing to explain the life-cycle labor market disparities. When firms face costs when posting vacancies, the long-term value of the match becomes important. An intuitive example concerns why skilled women have faced difficulties in finding jobs. Hsieh et al. (2019) point out that Justice Sandra Day O'Connor, like many women in the 1950s, had difficulties finding a job early in her career, despite being ranked third in her class at Stanford Law School. Justice Ruth Bader Ginsburg faced similar difficulties. A model of career choice, like the Roy model used by Hsieh et al. (2019), would have problems rationalizing high unemployment rates of high-skilled, willing-to-work women, just like Justices O'Connor and Ginsburg. Our search model with statistical discrimination can rationalize these situations. An average skilled woman in the 1950s had a high job separation rate, and a high average job separation rate lowers the expected long-term value of the match for firms. This weakens all labor market outcomes of skilled women, particularly job-finding and employment rates, as firms are less willing to hire workers with a low predicted match value.

We separately decompose skill, gender, and racial and ethnic gaps in labor market outcomes. Regarding the gaps in lifetime earnings, we find that wedges in human capital variables are more important when explaining skill gaps (74 percent), while search frictions are relatively more important in explaining gender gaps (46 percent) when compared to the determinants of the total gaps. Moreover, statistical discrimination accounts for 15 percent of the skill gap, 25 percent of the gender gap, and 31 percent of the racial and ethnic gap in lifetime earnings, emphasizing the larger role of discrimination as a determinant of gender and racial gaps.

Our findings suggest that statistical discrimination is potentially a more important source of discrimination than prejudice, although taste-based discrimination remains potentially important for certain groups and certain outcomes, such as for the job-finding rates of Black males and Asian females. This conclusion is consistent with a variety of micro evidence including List (2004), Levitt (2004), and Ewens, Tomlin, and Wang (2014). Lang and Lehmann (2012) reach a similar conclusion in their review of the existing literature. Based on the survey and micro-evidence, they argue that any theory of discrimination should rely on "either strong prejudice in only a small portion of the population or widespread mild prejudice" (p. 970).

Separation rates are exogenous in our model, and differences in separation rates among demographic groups are the underlying source of statistical discrimination. Our findings suggest that models of statistical discrimination—such as those in Coate and Loury (1993), Rosen (1997), Moro and Norman (2004), Gayle and Golan (2012), and Jarosch and Pilossoph (2019)—provide promising lines of research for understanding labor market disparities. As this literature makes clear, statistical discrimination may be individually rational but not necessarily socially optimal. We discuss in more detail other related literature in Section 7.

The remainder of the paper is organized as follows. Section 2 presents the model, while Section 3 describes the differences in labor market outcomes between demographic groups. Section 4 explains the calibration strategy, Section 5 reports the calibration and decomposition results, and Section 6 reports robustness checks. Finally, Section 7 provides a literature review, and Section 8 concludes.

2 Model

2.1 Model Setup

Consider a version of the DMP search and matching model extended to include heterogeneous workers and segmented labor markets. The extended model also features a life cycle with a finite horizon, learning by doing, and a nonparticipation state. Time is discrete and age is denoted by a, where $a \in A \equiv [\underline{a}, \bar{a}]$. The model focuses on the working years, which are the years between education and retirement.

Workers. Individuals enter the labor market at age $\underline{a}$, retire at age a_R, and die at age $\bar{a}$, where $\bar{a} > a_R$. We call individuals who have not retired *workers*. At any point in time a worker is either employed, $\overline{E}$, unemployed, $\overline{U}$, or nonparticipating, $\overline{N}$. Let $s \in S \equiv \{\overline{E}, \overline{U}, \overline{N}\}$ denote the labor market status of a worker. Workers enter the labor market without work experience and gain experience by working. Let $e \in [0, \bar{a} - \underline{a}]$ denote years of experience of a worker. Experience increases by one unit during each period of employment, $e_{a+1} = e_a + 1$, and each nonworking period keeps experience constant, $e_{a+1} = e_a$. Workers also belong to a demographic group i defined by gender (female, male), skill level (skilled, unskilled), and race and ethnicity (non-Hispanic Asian, non-Hispanic Black, Hispanic, and non-Hispanic White). We thus combine all workers with Hispanic ethnicity into one group regardless of their race, and the other groups defined by race include the members of the corresponding racial groups who are not Hispanic. For simplicity, we use "race" to refer to these four racial and ethnic groups from now on. As i determines the three dimensions of a worker's demographics, an example of i could be a skilled Black female. Let I denote the set of demographic groups. A worker is fully identified by her years of experience (e), age (a), labor market status (s), and demographic group (i). Denote by $x = (e, a, s, i)$ the state, or type, of a worker, where $x \in [0, \bar{a} - \underline{a}] \times [\underline{a}, a_R] \times S \times I$ and let $x' = (e+1, a+1, s', i)$. The state of a retiree is defined as $x_R = (e, a_R, \overline{N}, i)$.

Let $m(x)$ be the mass of workers of type x. The initial mass distribution, $m_i^s(0, \underline{a})$ is taken as given for all s and i. Workers transition into unemployment and nonparticipation at exogenous rates $\bar{\pi}_{EU}(x)$, $\bar{\pi}_{EN}(x)$, $\bar{\pi}_{UN}(x)$, and $\bar{\pi}_{NU}(x)$, and into employment at endogenous rates $\bar{\pi}_{NE}(x)$ and $\bar{\pi}_{UE}(x)$. Workers seek to maximize their expected present value of consumption. They are risk neutral and discount the future according to the discount factor $\beta \in (0, 1)$. Let $c(x)$ and $w(x)$ denote consumption and wages of type x, respectively. There are no savings, which implies that $c(x)$=$w(x)$ for employed workers. Wages of employed workers are determined by Nash bargaining between workers and firms, while consumption of non-employed workers and retirees are given by $\bar{c}(x)$, an exogenous parametric form. For completeness, it is convenient to assume that consumption of unemployed workers equals consumption of nonparticipating workers, $\bar{c}_i^{\bar{U}}(e,a) = \bar{c}_i^{\bar{N}}(e,a)$, which allows us to use a concise notation when describing the solution for wages. For simplicity, we do not explicitly describe the domain of each function whenever it is clear. For example, $w(x)$ refers to the wages of the employed workers only, $x = \left(e, a, \bar{E}, i\right)$.[9]

Human capital: Human capital of a worker, $h(x)$, is of the general type. There is no firm-specific human capital. We assume the following functional form for the human capital:

$$h(x) = y_i \exp\left(r(x)\, e\right), \tag{1}$$

where y_i is the baseline level of human capital that a member of a group i has when entering the labor market, and $r(x)$ are type-specific returns to experience. Both y_i and $r(x)$ are exogenous. We interpret y_i as education-related human capital, the human capital of a new worker for whom $e = 0$. Differences in baseline human capital, y_i, and returns to experience, $r(x)$, across types can then capture differences in the quality and quantity of education between demographic groups, differences in occupations and industries in which a representative worker of each type works, and discrimination. Central to our accounting exercise is to calibrate parameters y_i and $r(x)$ for all x.

The chosen functional form of human capital assumes that the post-schooling human capital formation is of the learning-by-doing type as in Barlevy (2008), Yamaguchi (2010), and Bagger et al. (2014). The human capital of a worker increases automatically whenever she is employed and producing. We could instead assume that the investment in human capital and working are competing, mutually exclusive activities as in models using the Ben-Porath type of human capital accumulation. However, Heckman, Lochner, and Cossa (2003) argue that it is difficult to distinguish between learning-by-doing and on-the-job training (Ben-Porath) human capital accumulation based on empirical evidence, so we choose to model the human capital accumulation based on a learning-by-doing approach. Learning-by-doing human capital accumulation is also supported by the empirical evidence showing the scarring effects of non-employment periods on wages (see more on the literature review in Section 7).

Firms and labor markets: There is a continuum of infinitely lived firms that seek to maximize their expected present value of profits net of hiring costs. Firms are risk neutral and discount the future at the same rate as workers do. Labor markets are assumed to be perfectly segmented across worker types. Firms can freely enter any of the segmented markets. Firms post vacancies for long-term positions at a cost $\kappa(x)$ per vacancy, a cost that may depend on a worker's type. Once a firm is matched with a worker, a worker produces $h(x)$ units of output per period, while gross per-period profits of the firm are $h(x) - w(x)$. A match is destroyed exogenously at a rate $d(x)$.

The assumption about segmented labor markets requires some discussion, as it may seem strong at first glance. First, segmentation is needed for the model to match key fea-

[9] We maintain various convenient assumptions of the canonical DMP model such as zero savings, exogenous job separation rates, and exogenous consumption of the non-employed. The focus of the model is on determining employment and unemployment rates, wages, and job-finding and labor market tightness rates for all types of workers, as defined by x.

tures of the data, such as differential job-finding rates between demographic groups, as we will show. Second, while various laws (e.g., the Civil Rights Act and the Employment Act) forbid differential treatment of workers in the U.S. labor markets based on, for example, workers' race, gender, and age, discriminatory behavior is hard to prove in practice. The evidence suggests that anti-discriminatory laws have had limited success (Valfort, 2018).[10] Third, in the absence of discrimination, segmentation would still be required for allocations to be efficient. Last but not least, allowing for segmentation of labor markets in the model does not create discrimination—it merely makes discrimination possible. Workers with similar characteristics facing nonprejudiced employers should display similar labor market outcomes even if markets are segmented. For these reasons, and because we are specifically interested in studying whether discrimination is needed for the model to match the observed labor market gaps, we choose to study segmented labor markets.

Matching technology*:* A worker and a firm with a vacant position are randomly matched in each of the submarkets according to the matching technology $M\left(u(x), v(x); x\right)$, where $u(x)$ and $v(x)$ are the masses of workers and firms, respectively, searching in a particular labor market. We assume that all unemployed workers search for a job, employed workers do not search, and a fraction $\psi\left(x\right) < 1$ of nonparticipants search.[11]

Thus, the mass of workers searching at a given employment status can be defined as follows:

$$u(x) \equiv \left\{ \begin{array}{c} m(x), \text{ if } s = \overline{U}, \\ \psi\left(x\right) m(x), \text{ if } s = \overline{N}, \\ 0 \text{ otherwise.} \end{array} \right\} \tag{2}$$

We assume that the matching technology adopts a standard Cobb-Douglas form $M(u, v; x) = A\left(x\right) u^{\alpha} v^{(1-\alpha)}$, where $A(x)$ represents the efficiency of the matching technology and is allowed to depend on a worker's type. Differences in matching efficiency across types reflect search frictions associated with particular labor markets. Once a match is formed, the output of the match is distributed according to a Nash bargaining solution in which a worker's bargaining power is given by $\phi\left(x\right)$.

Let $\theta\left(x\right) \equiv \frac{v(x)}{u(x)}$ denote the tightness of a particular labor market, the number of vacancies per job seeker. A firm's probability of filling a vacancy is given by $q(x) = M\left(u(x), v(x); x\right)/v\left(x\right) = A\left(x\right)\left(\theta\left(x\right)\right)^{-\alpha}$, and a non-employed worker's probability of finding a job is $f\left(x\right) = M\left(u(x), v(x); x\right)/u\left(x\right) = A\left(x\right)\left(\theta\left(x\right)\right)^{1-\alpha}$. These expressions make it clear that job-finding rates are solely the functions of labor market tightness rates and the efficiencies of the matching function.

The following assumption will guarantee that each match generates a strictly positive surplus:

Assumption 1 $h(x) > \bar{c}(x)$ and $c\left(x_R\right)$ increases (weakly) with experience.

This first part of the assumption is standard. The human capital of a worker is strictly

[10]As noted by Lang and Lehmann (2012, p. 970), almost all models they review implicitly assume such illegal practices.

[11]Job-to-job search is suboptimal in the model given that there is no expected gain from a match break.

greater than the consumption during non-employment for any given type x. The second part reinforces the benefit of remaining in a match as pensions (weakly) increase with experience. Both parts of the assumption are required to guarantee that a match generates a positive surplus.

Statistical discrimination: The notion that employers use statistics specific to a demographic group when assessing a worker's prospects is present in the model through the job destruction rates $d(x)$. Firms in a given market x can perfectly forecast the human capital of the worker they are looking to hire conditional on the worker staying in the match, but the expected duration of the match depends on job destruction rates, $d(x)$, specific to that market. Statistical discrimination arises if $d(x)$ is a function of i, the demographic identifier. In that case, job destruction rates may vary based on i, creating variation in the long-term values of the matches between a worker and a firm. To assess the extent to which statistical discrimination is prevalent in labor markets from the point of view of the model, we assume that firms and workers observe only a noisy signal of the true job destruction rate of a group x. The true job destruction rate is determined as $\bar{d}\,(x) \equiv \bar{\pi}_{EU}\,(x) + \bar{\pi}_{EN}\,(x)$, where $\bar{\pi}_{EU}\,(x)$ is the transition probability of a worker from employment to unemployment, and $\bar{\pi}_{EN}\,(x)$ is the transition probability from employment to nonparticipation. Firms and workers observe $d\,(x)$=$\mu\bar{d}\,(x) + (1-\mu)\,\hat{d}\,(x)$, where $\mu \in [0,1]$ is a parameter and $\hat{d}\,(x)$ is a reference job destruction rate common among all groups. For example, $\hat{d}\,(x)$ could be the average job destruction rate across demographic groups or it could be the job destruction rate of a reference group such as White males. The same holds true for workers. Workers observe $\pi_{EU}\,(x) \equiv \mu\bar{\pi}_{EU}\,(x) + (1-\mu)\,\hat{\pi}_{EU}\,(x)$ and $\pi_{EN}\,(x) \equiv \mu\bar{\pi}_{EN}\,(x) + (1-\mu)\,\hat{\pi}_{EN}\,(x)$, where $\hat{\pi}_{EU}\,(x)$ and $\hat{\pi}_{EU}\,(x)$ are defined analogously to $\hat{d}\,(x)$. At one extreme, firms can engage in perfect statistical discrimination based on workers' demographic group i when $\mu = 1$. Firms can post vacancies and negotiate wages based on average, group-specific job destruction rates and, consequently, based on the accurate long-term values of the matches. At the other extreme, if $\mu = 0$, firms can only use job destruction rates of the reference group, common for all demographic groups. Parameter μ will be calibrated.[12]

Gaps in the reverse-engineered parameters and taste-based discrimination: Before moving to the recursive formulation of the model, it is convenient to briefly explain the main goal of the paper in light of the setup just described. We use the model's solution to calibrate and reverse engineer the key model parameters: μ, y_i, $r(x)$, $\kappa\,(x)$, $A(x)$, $\phi\,(x)$, and $\psi\,(x)$. Reverse engineering is a step further from calibration in the sense that it seeks to match complete sequences of wages and job-finding rates of different groups over the entire life cycle, not only some selected moments or stylized facts. The reverse-engineering results are then used to calculate and interpret gaps in parameters across gender, race, age, and skill. Finally, using the obtained gaps in the parameters, we perform counterfactual

[12]One can interpret $1-\mu$ as the degree of firms' compliance with anti-discrimination laws. For example, when $\mu = 0$, firms are still able to post vacancies and negotiate wages contingent on workers' human capital but are unable to differentiate workers in terms of their expected match length. This would eliminate statistical discrimination based on, for example, women's higher likelihood of exiting the labor force because of family reasons.

exercises to quantify the importance of each gap in explaining the distinct labor market outcomes of demographic groups.

The reverse-engineered and calibrated gaps represent the underlying fundamental sources of unequal labor market outcomes among demographic groups, according to the model. By separating human capital differentials from other gaps in the underlying parameters, the model suggests potential discriminatory behavior underlying a number of these parametric gaps. Taste-based discrimination during the hiring process could be linked to gaps in matching efficiencies, search efficiencies of nonparticipants, and in vacancy posting costs (parameters $A(x)$, $\kappa(x)$, and $\psi(x)$), while taste-based discrimination during employment could be linked to gaps in parameters $r(x)$ and $\phi(x)$, parameters representing returns to experience, and the bargaining power of workers.

2.2 Recursive Formulation

2.2.1 A Firm's Problem

Let $\bar{V}$ be the value of a firm without a worker and $J(x)$ be the value of a firm with a worker of type $x = \left[e, a, \overline{E}, i\right]$. Then

$$J(x) = \left\{ \begin{array}{c} h(x) - w(x) + \beta \left[d(x)\bar{V} + (1 - d(x)) J(x')\right] \\ \text{if } \underline{a} \leq a < a_R - 1, \\ h(x) - w(x) + \beta \bar{V} \text{ if } a = a_R - 1 \end{array} \right\}.$$

The first part of the expression states that the value of a firm with a worker is the flow of gross profits plus the discounted continuation value of the match. The continuation value consists of the value of posting a new vacancy, $\bar{V}$, if the match is destroyed, which occurs with probability $d(x)$, and the value of remaining in the match, $J_i(e+1, a+1)$, which occurs with probability $1-d(x)$. The second part of the expression states that a firm with a worker who is about to retire will become a firm without a worker in the following period.

The value of a firm posting a vacancy in market x is

$$V(x) = \max\left\{-\kappa(x) + \beta\left[q(x) J_i(e, a+1) + (1 - q(x))\bar{V}\right], 0\right\}.$$

The maximum value of posting a vacancy in any labor market is then given by

$$\bar{V} = \underset{x}{max}\left\{V(x), 0\right\}.$$

Free entry of firms into any labor market guarantees that the values of unfilled vacancies must all be equal to zero: $V(x) = 0$ for all feasible x. As a result, the maximum value of posting a vacancy must be zero as well, $\bar{V} = 0$. Active firms are thus indifferent in which type of a worker to hire and in which of the segmented markets to operate if the free entry condition holds.[13]

[13]Potential prejudiced employers may still operate in markets they do not prefer if, for example, negotiated wages in that market are sufficiently low for firms to break even.

The problem of a firm with a worker then simplifies to

$$J(x)=\left\{\begin{array}{c} h\left(x\right)-w\left(x\right)+\beta\left(1-d\left(x\right)\right)J\left(x'\right) \\ \text{if } \underline{a}\leq a<a_R-1, \\ h\left(x\right)-w\left(x\right)\ \text{ if } a=a_R-1 \end{array}\right\}, \tag{3}$$

while for firms posting vacancies simplifies to

$$\kappa\left(x\right)=\beta q\left(x\right)J_i\left(e,a+1\right)=\beta f\left(x\right)\theta\left(x\right)^{-1}J_i\left(e,a+1\right)\ \text{ for } \underline{a}\leq a<a_R-1. \tag{4}$$

The last equation states that the expected present value of filling a vacancy must be just enough to recover the costs of posting the vacancy.

2.2.2 A Worker's Problem

Consider now the (maximum) expected present value of earnings of an employed worker, E, an unemployed worker, U, a nonparticipating worker, N, and a retired worker, R. The expected present value of consumption of a newly retiree simply satisfies

$$R\left(x_R\right)=\sum_{i=a_R}^{\overline{a}}\beta^{i-a_R}\overline{c}(x_R)=\frac{1-\beta^{\overline{a}-a_R-1}}{1-\beta}\overline{c}(x_R), \tag{5}$$

where $\overline{c}(x_R)$ is consumption of a retiree of type x_R. Like firms, workers do not necessarily know their true match break probabilities and use the weighted average match break probabilities $\pi_{EU}(x)$ and $\pi_{EN}(x)$ in their value functions. The corresponding value functions E, U, and N can then be written recursively as

$$E(x)=\left\{\begin{array}{c} w(x)+\beta\left[\begin{array}{c}\pi_{EU}(x)U(x')+\pi_{EN}(x)N(x') \\ +(1-\pi_{EU}(x)-\pi_{EN}(x))E(x')\end{array}\right] \\ \text{if } \underline{a}\leq a<a_R-1 \\ w(x)+\beta R_i\left(e+1,a_R,\overline{N}\right)\ \text{ if } a=a_R-1 \end{array}\right\}, \tag{6}$$

$$U(x)=\left\{\begin{array}{c} \overline{c}(x)+\beta\left[\begin{array}{c}f(x)E_i(e,a+1)+\overline{\pi}_{UN}(x)N_i(e,a+1) \\ +(1-f(x)-\overline{\pi}_{UN}(x)U_i(e,a+1)\end{array}\right] \\ \text{if } \underline{a}\leq a<a_R-1 \\ \overline{c}(x)+\beta R_i\left(e,a_R,\overline{N}\right)\ \text{ if } a=a_R-1 \end{array}\right\}, \tag{7}$$

$$N(x)=\left\{\begin{array}{c} \overline{c}(x)+\beta\left[\begin{array}{c}f(x)E_i(e,a+1)+\overline{\pi}_{NU}(x)U_i(e,a+1) \\ +(1-f(x)-\overline{\pi}_{NU}(x))N_i(e,a+1)\end{array}\right] \\ \text{if } \underline{a}\leq a<a_R-1 \\ \overline{c}(x)+\beta R_i\left(e,a_R,\overline{N}\right)\ \text{ if } a=a_R-1 \end{array}\right\}, \tag{8}$$

The interpretation of these functionals is intuitive. An employed worker consumes her wage $w(x)$ each period. A match between a worker and a firm can be destroyed in two ways: with (perceived) probability $\pi_{EU}(x)$, a worker becomes unemployed, and with probability $\pi_{EN}(x)$, the worker becomes a nonparticipant. The worker continues producing with probability $1-\pi_{EU}(x)-\pi_{EN}(x)$ and stays in the employment state. At the beginning of each period, an unemployed worker consumes $\bar{c}(x)$=$\bar{c}_i^{\bar{U}}(e,a)$. Next period, she finds a job with probability $f(x)=f_i(e,a,\bar{U})$, in which case she moves to the employment state. A worker may also move to nonparticipation with probability $\bar{\pi}_{UN}(x)$; otherwise, she will stay unemployed. A similar interpretation holds for the value function of a nonparticipating worker.

It is convenient to define the present value of lifetime earnings, or consumption, of a worker x as

$$W(x)=m_i^{\bar{E}}(e,a)\,E(x)+m_i^{\bar{U}}(e,a)\,U(x)+m_i^{\bar{N}}(e,a)\,N(x), \tag{9}$$

where $m_i^{\bar{E}}(e,a)$, $m_i^{\bar{U}}(e,a)$, and $m_i^{\bar{N}}(e,a)$ determine the masses of workers in each of these labor market states for any given experience and age.

2.2.3 Nash Bargaining

Wages in the model are negotiated through Nash bargaining. A firm and a worker share the match surplus $S(x)=E(x)-U(x)+J(x)$, given the bargaining weights $\phi(x)$ for the worker and $1-\phi(x)$ for the firm, in the following way:[14]

$$\underset{E-U,J}{max}(E-U)^{\phi(x)}J^{1-\phi(x)} \text{ subject to } S(x)=E-U+J,$$

and the solution for each labor market satisfies

$$J(x)=\Theta(x)\times(E(x)-U(x)) \text{ where } \Theta(x)=\frac{1-\phi(x)}{\phi(x)}. \tag{10}$$

2.3 Aggregate Labor Flows

Given the initial distribution of workers, $m_i^s(0,\underline{a})$, and job-finding rates $f(x)$ for all x, the subsequent distribution of workers $m(x)$ can be calculated assuming a law of large numbers. The mass of individuals with no experience at age $a\in[\underline{a},a_R-2]$ is determined as

$$\begin{aligned}
m_i^{\bar{E}}(0,a+1)&=f_i^{\bar{U}}(0,a)\times m_i^{\bar{U}}(0,a)+f_i^{\bar{N}}(0,a)\times m_i^{\bar{N}}(0,a);\\
m_i^{\bar{U}}(0,a+1)&=(1-\bar{\pi}_{UN}(x)-f_i^{\bar{U}}(0,a))\times m_i^{\bar{U}}(0,a)+\bar{\pi}_{NU}(x)\times m_i^{\bar{N}}(0,a);\\
m_i^{\bar{N}}(0,a+1)&=(1-\bar{\pi}_{NU}(x)-f_i^{\bar{N}}(0,a))\times m_i^{\bar{N}}(0,a)+\bar{\pi}_{UN}(x)\times m_i^{\bar{U}}(0,a).
\end{aligned} \tag{11}$$

[14] We assume that the outside option of a worker during wage bargaining is always unemployment, U. An alternative specification is to allow the outside option of the worker to be nonparticipation or a mix between unemployment and nonparticipation. As discussed in Córdoba, Isojärvi, and Li (2021), the efficiency of the solution requires the surplus of a new worker to be defined relative to the worker's previous state, before becoming employed, which could be either unemployment or nonparticipation. However, efficiency does not restrict how the surplus of production is divided between a firm and a worker with tenure in the job. For tractability, we assume a simple outside option, unemployment. This reduces the vector x but also implies that allocations in the model are not fully efficient.

Moreover, the mass of individuals with experience $e \in [1, a]$ at age $a \in [\underline{a}, a_R - 2]$ is determined as

$$\begin{aligned} m_i^{\bar{E}}(e, a+1) &= (1 - \bar{\pi}_{EU}(x) - \bar{\pi}_{EN}(x)) \times m_i^{\bar{E}}(e-1, a) + f_i^{\bar{U}}(e, a) \times m_i^{\bar{U}}(e, a) \\ &\quad + f_i^{\bar{N}}(e, a) \times m_i^{\bar{N}}(e, a); \\ m_i^{\bar{U}}(e, a+1) &= (1 - \bar{\pi}_{UN}(x) - f_i^{\bar{U}}(e, a)) \times m_i^{\bar{U}}(e, a) + \bar{\pi}_{NU}(x) \times m_i^{\bar{N}}(e, a) \\ &\quad + \bar{\pi}_{EU}(x) \times m_i^{\bar{E}}(e-1, a); \\ m_i^{\bar{N}}(e, a+1) &= (1 - \bar{\pi}_{NU}(x) - f_i^{\bar{N}}(e, a)) \times m_i^{\bar{N}}(e, a) + \bar{\pi}_{UN}(x) \times m_i^{\bar{U}}(e, a) \\ &\quad + \bar{\pi}_{EN}^{i}(x) \times m_i^{\bar{E}}(e-1, a). \end{aligned} \tag{12}$$

Notice that while the firms and the workers may not be sure about the accurate match break probabilities, $\bar{\pi}_{EU}$ and $\bar{\pi}_{EN}$, the actual flows into employment, unemployment, and nonparticipation evolve according to the actual probabilities.

2.4 Characterization of the Solution

We now characterize the solution for wages, labor market tightness rates, and job-finding rates using backward induction. In particular, we first obtain closed-form solutions for the last period of working life (see Appendix A for the solution), which we then use to find solutions for the previous periods.

2.4.1 Solution for $a < a_R - 1$

The solutions for periods $a < a_R - 1$ can be expressed in terms of workers' surpluses and value changes defined as

$$\begin{aligned} S_{EU}(x) &\equiv E(x) - U(x_i^{\bar{U}}(e, a));\; S_{EN}(x) \equiv E(x) - N(x_i^{\bar{N}}(e, a)); \\ S_{NU}(x) &\equiv N(x) - U(x_i^{\bar{U}}(e, a));\; S_{UN}(x) \equiv U(x) - N(x_i^{\bar{N}}(e, a)); \\ \Delta U(x) &\equiv U(x) - U_i(e-1, a);\; \Delta N(x) = N(e, a) - N_i(e-1, a). \end{aligned} \tag{13}$$

The following proposition provides a partial characterization of the solution for wages, tightness rates, and job-finding rates.

Proposition 1 The solutions for $w(x)$, $\theta(x)$, and $f(x)$, for $0 \leq a < a_R - 1$, satisfy

$$w(x) = \frac{h(x) + \Theta(x)\left[\bar{c}(x) + \beta\Omega(x)\right]}{1 + \Theta(x)}, \tag{14}$$

$$\theta(x) = \left[\frac{\beta A(x) J_i(e, a+1)}{\kappa(x)}\right]^{\frac{1}{\alpha}}, \text{ and} \tag{15}$$

$$f(x)^{\alpha} = \frac{A(x)}{\kappa(x)^{1-\alpha}} \left(\beta J_i(e, a+1)\right)^{1-\alpha}, \text{ where} \tag{16}$$

$$
\begin{aligned}
\Omega(x) &= f_i^{\bar{U}}(e,a) S_{EU}^i(e,a+1) + \bar{\pi}_{UN}(x) S_{NU}^i(e,a+1) \\
&\quad + \pi_{EN}(x)\left[S_{EN}(x') - S_{EU}(x')\right] - \Delta U^i(e+1,a+1), \\
J_i(e,a+1) &= \Theta(x)\, S_{EU}^i(e,a+1), \text{ and}
\end{aligned} \tag{17}
$$

$$
S_{EU}(x) = w(x) - \bar{c}_i^{\bar{U}}(e,a) + \beta \begin{bmatrix} (1-\pi_{EU}(x))\, S_{EU}(x') - \pi_{EN}(x) S_{EN}(x') \\ -\bar{\pi}_{UN}(x) S_{NU}^i(e,a+1) \\ -f_i^{\bar{U}}(e,a) S_{EU}^i(e,a+1) + \Delta U(x') \end{bmatrix}.
$$

Proof. See Appendix A.

The term $\beta\Omega(x)$ in equation (14) collects all net losses of remaining employed. Wages increase with $\Omega(x)$ to compensate workers for those losses to an extent determined by the workers' bargaining power. In particular, a higher job-finding probability, $f_i^{\bar{U}}$, increases wages since $S_{EU}^i(e,a+1) > 0$. Intuitively, the higher the chances of finding a new job, the higher the losses associated with remaining in the current job. Furthermore, the wage of a worker equals a worker's human capital if $\Theta(x) = 0$, while at the other extreme, the wage equals $\bar{c}_i^{\bar{U}}(e,a) + \beta\Omega(x)$ when $\Theta(x) = \infty$. According to these expressions, unequal wages among workers with identical human capital only arise if firms have some bargaining power, $\Theta(x) > 0$, and workers have different outside options or prospects. Workers with better outside options, as reflected by $\bar{c}_i^{\bar{U}}(e,a) + \beta\Omega(x)$, are paid more. *Unequal pay for an equal job*, the idea that $w(x_A) \neq w(x_B)$ even when $h(x_A) = h(x_B)$, arises naturally due to search frictions present in the model.

Equation (16) shows that a job-finding rate of a worker is a direct function of the economic value of the worker to the firm, $J_i(e,a+1)$. In general, it states that job-finding rates are higher in markets with more efficient matching, lower costs of posting vacancies, and higher values of active firms. Discrimination in hiring could arise through the term $\frac{A(x)}{\kappa(x)^{1-\alpha}}$: a particularly low matching efficiency for type x workers or an unusually high cost of hiring type x workers would lead to job-finding rates lower than what is justified by the economic value of the worker to the firm.

The key role of job separation rates and statistical discrimination can also be gauged from these expressions. Consider the effect of $\pi_{EU}(x)$ on wages and job-finding rates. For a given sequence of wages, an inspection of the formulas reveals that a higher $\pi_{EU}(x)$ reduces workers' surplus $S_{EU}(x)$ at state x but also at all states leading to state x. This reduces firms' incentives to post vacancies for those types of workers. Lower surpluses also lower wages, according to (14), but only of wages in previous periods leading up to state x. Current and future wages are not affected by a higher destruction rate at state x.

To gain some further intuition about the determination of wages, consider the determination of wages two periods before retirement. Denote by $x_{R-2} = x(e, a_R - 2, \bar{E}, i)$ and assume that $\bar{c}(x) = \bar{c}$ for all x. As shown in Appendix A.3, the wages then are

$$
w(x_{R-2}) = \frac{h(x_{R-2}) + \Theta(x_{R-2})\left[\bar{c} + \beta f_i^{\bar{U}}(e, a_R - 2)\,(w(x_{R-1}) - \bar{c})\right]}{1 + \Theta(x_{R-2})}.
$$

This expression illustrates the determination of wages and, in particular, the role of the job-finding rate. A higher current job-finding rate tends to increase current wages if workers have some bargaining power. If $\Theta(x_{R-2}) = 0$, then $w(a_{R-2}) = h(a_{R-2})$. At the other extreme, if $\Theta(x_{R-2}) = \infty$, then

$$w(x_{R-2}) = \bar{c} + \beta f_i^{\bar{U}}(e, a_R - 2)\left(w(x_{R-1}) - \bar{c}\right),$$

a minimum wage that reflects the value of the outside option. In conclusion, in the presence of search frictions, wages do not reflect only the underlying true productivity of the worker. As a result, simple Mincer wage regressions will not provide a correct estimate of the underlying human capital trajectories of workers over the life cycle in the presence of search frictions and unemployment. In Section 4, we reverse engineer human capital trajectories of workers in different markets over the life cycle using the structure of the model. As expected from the previous discussion, our estimated human capital paths differ notably from wages for certain groups.

3 Stylized Facts and Basic Counterfactuals

3.1 Stylized Facts

We now highlight stylized features of the data regarding different demographic groups. Table 1 provides averages of the various labor market outcomes for the studied demographic groups, calculated using IPUMS (2018) data for individuals between the ages 25 and 65. Figure 2, presented in the Introduction, and Figure 3 portray corresponding life-cycle profiles of the outcomes.

Table 1 documents some well-known facts. Whites, males, and the skilled tend to exhibit better labor market outcomes compared to minority[15] groups, females, and the unskilled. They have higher wages and higher employment and job-finding rates, lower unemployment and job separation rates, and, overall, higher average lifetime earnings. There are some important exceptions to this characterization. Skilled Asian males outperform other groups in wages and earnings, while Hispanic males, skilled and unskilled, do particularly well compared to the other groups in terms of employment and job-finding rates. Labor market outcomes of Black males are problematic: they have the highest unemployment rate, both among the skilled and the unskilled, the highest separation rate to unemployment, and unusually high nonparticipation rates among males. Black males also have the second-lowest job-finding rate of the unskilled, and the third-lowest wage rate of the skilled.

Consider next the full life-cycle profiles. Figure 2 shows persistent wage gaps between groups over the entire life cycle with a few but important exceptions. For each gender-race pair, life-cycle wage growth shows the well-known pattern: wages grow rapidly for young workers, flatten, then start to decrease later in the career. Wages for both Asian males and

[15]For the sake of simplicity, we refer to racial groups other than non-Hispanic Whites as minorities.

Table 1: Descriptive statistics and basic counterfactuals (IPUMS, 2018).

Groups	Pop. share	Wage ($/hour)	Employ. rate	Unemp. rate	Non-Part. rate	π_{UE}	π_{EU}	π_{EN}	Earnings (W)
White male	31.0%	30.1	80.3%	3.5%	16.2%	49.7%	2.1%	4.0%	89.3
Skilled	19.2%	34.5	84.9%	2.9%	12.2%	49.4%	1.7%	3.3%	106.0
Unskilled	11.9%	21.8	73.0%	4.5%	22.5%	49.8%	3.0%	5.3%	60.1
White female	31.2%	23.3	67.8%	2.7%	29.6%	44.8%	1.6%	6.9%	62.0
Skilled	20.3%	26.4	72.6%	2.4%	25.0%	47.3%	1.5%	6.3%	73.3
Unskilled	10.9%	16.4	58.6%	3.3%	38.2%	40.3%	2.1%	8.5%	42.1
Black male	6.2%	21.7	65.1%	6.6%	28.3%	38.9%	3.9%	7.6%	58.5
Skilled	2.9%	25.6	73.6%	5.7%	20.7%	41.5%	3.2%	5.9%	73.6
Unskilled	3.2%	17.2	57.0%	7.7%	35.3%	36.8%	4.9%	9.6%	44.0
Black female	6.7%	19.5	62.7%	5.2%	32.1%	35.4%	2.9%	8.6%	51.5
Skilled	3.6%	22.8	70.6%	4.6%	24.8%	39.1%	2.4%	7.2%	64.3
Unskilled	3.1%	14.5	52.9%	6.2%	40.9%	31.9%	3.7%	10.8%	35.9
Asian male	3.5%	32.6	81.1%	3.6%	15.3%	42.0%	1.8%	4.9%	92.8
Skilled	2.2%	37.3	82.7%	3.4%	13.9%	40.7%	1.5%	4.5%	109.1
Unskilled	1.3%	18.5	77.1%	4.7%	18.2%	42.6%	2.7%	5.8%	52.4
Asian female	3.7%	25.3	64.1%	2.7%	33.2%	35.3%	1.5%	8.6%	64.6
Skilled	2.4%	29.4	67.4%	2.8%	29.8%	34.6%	1.4%	7.9%	78.1
Unskilled	1.3%	14.6	58.7%	2.7%	38.6%	36.8%	1.6%	11.3%	37.6
Hispanic male	9.0%	20.7	78.4%	4.9%	16.7%	56.0%	3.6%	5.6%	59.3
Skilled	3.0%	28.0	81.5%	4.3%	14.3%	48.5%	2.5%	4.5%	83.0
Unskilled	6.1%	16.9	76.6%	5.4%	18.0%	58.2%	4.1%	6.1%	47.1
Hispanic female	8.6%	17.7	56.1%	4.0%	39.9%	38.8%	2.6%	11.7%	44.7
Skilled	3.3%	22.9	68.0%	3.7%	28.3%	40.2%	2.0%	8.0%	63.0
Unskilled	5.4%	13.6	49.2%	4.3%	46.5%	37.8%	3.2%	14.6%	33.4
Ratio									
Skill ratio	0.76	0.60	0.83	1.48	1.58	0.96	1.75	1.55	0.55
Gender ratio	1.01	0.80	0.83	0.79	1.80	0.86	0.77	1.70	0.73
Race ratio	0.61	0.79	0.91	1.55	1.23	0.89	1.57	1.50	0.76
Average gains from eliminating demographic gaps (% increase)									
Skill gap		20.9%	7.9%	-17.2%	-20.1%	1.8%	-24.6%	-19.1%	24.4%
Gender gap		11.5%	9.3%	12.1%	-28.7%	7.6%	13.1%	-26.1%	15.6%
Race gap		8.5%	3.7%	-17.1%	-7.9%	4.3%	-17.8%	-15.7%	10.0%
All gaps		42.4%	18.9%	-23.2%	-50.7%	9.3%	-29.1%	-49.5%	54.7%

Notes: Displayed average outcomes are based on authors' calculations using Current Population Survey data (IPUMS, 2018) for the years 1998 to 2018 and individuals between the ages 25 and 65. The 2018 population shares in the second column are calculated using data from U.S. Census Bureau (2019) and IPUMS (2018). In addition to population shares, the table shows the hourly wage rates; employment, unemployment, and nonparticipation rates; quarterly job-finding rates for the unemployed (π_{UE}); job separation rates to unemployment (π_{EU}) and nonparticipation (π_{EN}); and present value of lifetime earnings (W). W is calculated using equation (9). The displayed ratios are calculated as follows: Skill ratio = population-weighted average of outcomes of the unskilled/ population-weighted average of outcomes of the skilled; Gender ratio = population-weighted average of female outcomes / population-weighted average of male outcomes; Race ratio = population-weighted average of non-White (minority) outcomes / population-weighted average of White outcomes.

females have slightly different patterns in the CPS data compared to other groups: their wages peak earlier, around age 40, and start to decrease after that. The between-group wage gaps are fairly small for young workers, but as the wage growth rates differ between groups, the wage gaps increase over the life cycle. Within race, males have higher wage growth rates compared to females, and Asians have the highest wage growth rate among each gender, followed by Whites and Blacks. An average White female has a very similar wage growth pattern as average Hispanic and Black males. Interestingly, Asian males and females have the highest wage growth rates early in life, along with White males, which partly arise because of the higher schooling level of an average Asian but also from higher initial returns to schooling, particular for Asian males.[16]

Figure 2 also shows the average unemployment and nonparticipation rates as well as job-finding rates for the unemployed for each gender-race pair. Unemployment rates are higher for younger workers, but decrease up to age 35 and stay fairly constant after that. White and Asian males and females have the lowest unemployment rates, while Black males and females have significantly higher unemployment rates over the whole life cycle, and especially when they are young. Hispanics do better in terms of unemployment rates compared to Blacks, but their rates are still high compared to Whites and Asians. Within race, Hispanic females have higher unemployment rates and Black females have lower unemployment rates compared to males, while the unemployment rates are fairly similar between White and Asian males and females.

Figure 2 reveals variation in life-cycle nonparticipation rates between groups. In general, nonparticipation rates are lower for younger workers but start to increase rapidly after age 55 for all groups. Females are more likely to be nonparticipating over the whole life cycle and especially before age 45. Within male groups, nonparticipation rates are quite similar over the whole life cycle, the only exception being Black males: they are more likely to be nonparticipating over the whole life cycle compared to other male groups, and their nonparticipation rate starts to increase earlier, around age 45. The nonparticipation rates of Black males are closer to the nonparticipation rates of female groups than other male groups after age 45. It is not clear why the nonparticipation patterns for Black males differ from the patterns of other male groups. An explanation could be higher the incarceration rate for Black males, but as CPS data typically exclude institutionalized people, the higher incarceration rate cannot solely explain this difference. There is more variation in the nonparticipation rates for within-female groups compared to within-male groups, Hispanic and Asian females being more likely to be nonparticipating compared to Black and White females, especially before age 45.

To conclude the patterns in the labor market outcomes shown in Figure 2, we see that unemployment and wage outcomes seem to be negatively correlated: the lower the unemployment rates, the higher the levels and growth rates of wages tend to be. However, while Hispanic males and females have lower unemployment rates and higher job-finding rates compared to Black males and females, their wages are lower. Thus, it seems that even

[16] We can confirm these stylized facts for Asian groups using Panel Study of Income Dynamics (PSID) data, although, due to the small sample size, the results are noisy.

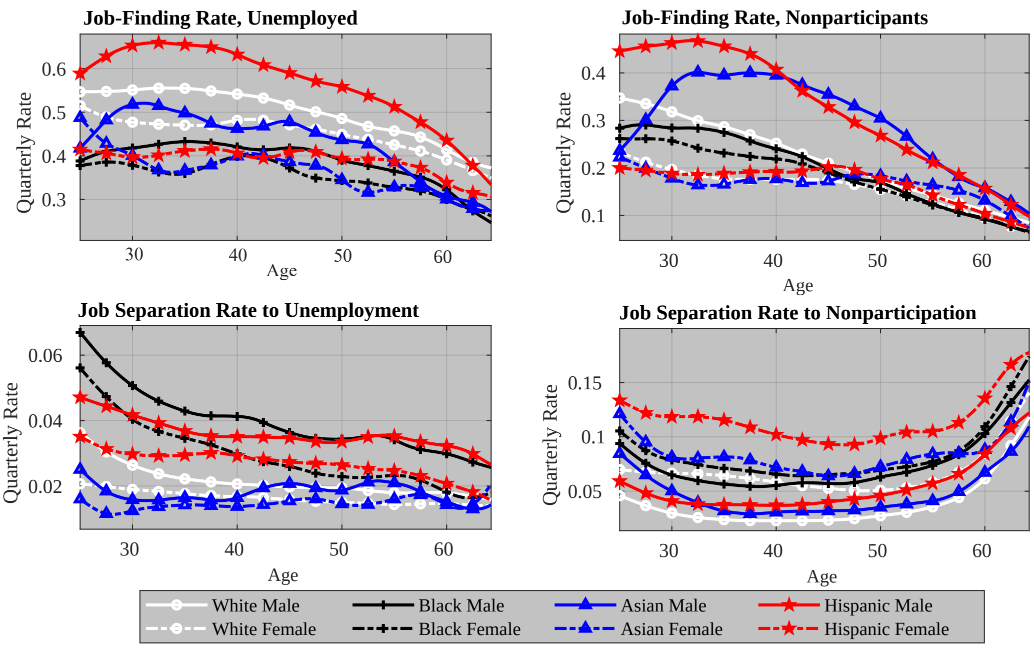
though Hispanics have relatively better employment outcomes compared to Blacks, their wages do not seem to reflect that.

Figure 3 presents the average quarterly transition flows between employment and unemployment, and employment and nonparticipation for each gender-race pair.[17] We observe large disparities in the job-finding rates between gender and racial groups. In general, job-finding rates are the highest for the young and prime-age workers, while the rates start to decline after ages 40 to 45. Overall, males tend to have higher job-finding rates compared to females, especially during the prime working years, but the job-finding rates of Black males are closer to the rates of female groups than other male groups. Hispanic males have notably high job-finding rates over the whole life cycle compared to any other group. While Asian females have very strong labor market outcomes in terms of wages and unemployment, their job-finding rates are surprisingly the lowest of all the groups, along with Black females.

The greatest difference between job-finding rates of males and females within each race occurs between ages 25 and 45: while males' job-finding rates are at their highest level for every group, females' job-finding rates slightly decrease. Asian and Black females have especially low job-finding rates between ages 30 and 40. In general, job-finding probabilities for the unemployed are overall higher for all groups when comparing to job-finding probabilities for nonparticipants, which demonstrates that these two groups should be treated separately.

Figure 3 shows that job destruction rates to unemployment and nonparticipation differ greatly with gender. While females are typically more likely to leave employment to nonparticipation, especially during the prime working years, this result reverses when looking at the job destruction rates to unemployment. Males are more likely to move from employment to unemployment when comparing the rates within a race. Job destruction rates to unemployment are higher early in the life cycle but stay relatively constant from ages 35 to 55 for all the groups, except for Blacks, whose job destruction probabilities show a decreasing trend over the whole life cycle. Both Black males and females are the most likely groups to move from employment to unemployment within gender, followed by Hispanics. Young Blacks have an especially high likelihood of moving from employment to unemployment compared to any other group. Also, Black males are notably more likely to move to nonparticipation compared to other male groups, which is consistent with the higher nonparticipation rate for Black males shown in Figure 2. Black males are almost twice as likely to move from employment to nonparticipation during the prime working ages compared to White males, and the flows from employment to nonparticipation for Black males seem to be somewhat closer to the ones of Black and White females than the ones of other males. To conclude, females are more likely to move to nonparticipation over the life cycle compared to males, and Blacks have considerably higher job destruction rates compared to other races.

[17] As mentioned, we also estimate the transition flows separately for both skilled and unskilled groups, and we use those flows in the model calibration.



Notes: These job-finding and job separation rates are based on the authors' calculations using IPUMS (2018) data for the years 1998 to 2018.

Figure 3: Average quarterly job-finding and job separation rates over the life cycle for different demographic groups.

3.2 Skill Premium, Gender Gaps, and Racial Gaps in Labor Market Outcomes

Table 1 also reports skill, gender, and race ratios in the labor market outcomes. Skill ratios are calculated as the population-weighted average of the outcomes of the unskilled relative to the skilled. For example, the wage ratio of 0.60 signifies that the unskilled average wage is 60 percent of the skilled average wage. Gender ratios similarly refer to the average outcomes of females relative to the average outcomes of males, while race ratios refer to the average outcomes of minorities relative to those of Whites. These ratios provide concise evidence of the large gaps between various demographic groups in a variety of labor market outcomes. In terms of average lifetime earnings (W), the unskilled earn 45 percent less than the skilled, females earn 27 percent less than males, and minorities earn 24 percent less than Whites. Gaps in lifetime earnings are due to gaps in both wages and employment. The unemployment rate is 48 percent higher for the unskilled, 21 percent lower for females, and 55 percent higher for minorities.

The last part of Table 1 reports simple counterfactual effects of eliminating skill, gender, and racial gaps, one by one, on the economy-wide averages of various labor market outcomes. The counterfactual that eliminates gender gaps assumes that females achieve the same labor market outcomes as their male counterparts of the same skill, age, and race. The counterfactual eliminating the racial gaps assumes that minority groups have the same labor market outcomes as their White counterparts of the same gender, age, and skill. Finally, the counterfactual that eliminates skill gaps assumes that unskilled individuals achieve the same outcomes as their skilled counterparts of the same age, gender, and race. The potential aggregate impacts of eliminating these gaps in the labor market outcomes are significant. For example, average lifetime earnings could increase by 24 percent if skill gaps were eliminated, 16 percent if gender gaps were eliminated, and 10 percent if racial gaps were eliminated. These simple counterfactual results indicate that the aggregate benefits of closing or reducing these gaps could be significant.

4 Calibration and Reverse Engineering of Model Parameters

4.1 Standard Parameters

We set the model time period to be a quarter and the discount rate to be $\beta = 0.9902$, which implies that the real interest rate equals 4 percent annually. We concentrate on workers between ages 25 and 65 and assume that people live until age 80. Thus, $\underline{a} = 0$ (age 25), $a_R = 163$ (age 65), and $\bar{a} = 319$ (age 80). We assume that at age 25, the initial mass one of workers, $m_i^s(0, \underline{a})$, is divided between employment, unemployment, and nonparticipation so that the values match the average values for each group i observed in the CPS data between 1998 and 2018. We calibrate the model for 24 types of i: we first calibrate the model for eight different gender (male and female) and race (non-Hispanic Asian, non-Hispanic Black, Hispanic, and non-Hispanic White) groups and then separately for 16 different gender-race-skill groups, where the level of skill can be either skilled or unskilled, as defined in the previous sections. We set the elasticity of the matching function, α, to be equal to 0.5, a common value used in the search literature (e.g., Shimer (2005)).

The parameter capturing the degree of statistical discrimination, μ, is calibrated such that the White/Black male ratio of vacancies per unemployed equals 1.5, consistent with the findings of Bertrand and Mullainathan (2004). We find that matching that calibration target requires setting $\mu = 1$, which implies that, in the model, firms need to be allowed to accurately use the group-specific job destruction rates so that the calibration target can be matched. Our baseline model specification then allows for full statistical discrimination. Section 6.1 provides a comparison with the alternative case, $\mu = 0$, and explains in detail why full statistical discrimination better describes the data in the light of the model.

4.2 Matching Productivities and Human Capital

The main stylized facts that we require the model to exactly replicate are the life-cycle profiles of wages and job-finding rates for each group i, as illustrated in the first panel of Figure 2 and panels 1 and 2 of Figure 3. The key equations for this purpose are (3), (16), (21), and (14). Given a value of $J_i(e, a+1)$, which can be obtained by backward induction starting at the retirement age, equation (16) provides a connection between job-finding rates and the ratio $A(x) / (\kappa(x))^{1-\alpha}$. Given the series of job-finding rates, only partial identification of this ratio is possible. It is not possible to determine, for example, if an unusually low job-finding rate—one that is below what is justified by the value of the match to the firm, J—is due to a particularly low matching productivity or a particularly high cost of posting a vacancy. We follow the literature by assuming that $\kappa(x)$ solely depends on the human capital of the worker, which implies, for example, that it is more costly to hire a skilled worker than an unskilled worker. In particular, we assume that $\kappa(x) = \bar{\kappa}h(x)$, where $\bar{\kappa}$ is a constant. This formulation precludes any discrimination to be captured by $\kappa(x)$, since the cost of hiring a worker only depends on the true productivity of the worker. This formulation confers a convenient scale invariance, or a balanced growth, property to the model: equilibrium allocations are invariant to scaling human capital levels by a nonnegative factor. This can be seen from equation (16): doubling human capital would double the value of a firm with workers, J, but also the cost of hiring workers, $\kappa(x)$, leaving the labor market tightness rate unchanged.

Equation (16) can be used to solve for $A(x)$ as

$$A(x) = f(x)^{\alpha} \left(\frac{\bar{\kappa}h(x)}{\beta J_i(e, a+1)} \right)^{1-\alpha}. \tag{18}$$

According to this expression, matching efficiency reflects the job-finding rate and the cost-benefit ratio, $\frac{\bar{\kappa}h(x)}{\beta J_i(e,a+1)}$, of that particular market x. Labor markets with unusually low job-finding rates, but normal cost-benefit ratios, are particularly inefficient when it comes to matching. Any discriminatory behavior in hiring is thus, by construction, captured by the efficiency parameter $A(x)$ as unusually low matching productivity. Similarly, markets with normal job-finding rates but unusually low cost-benefit ratios are also particularly inefficient. An alternative formulation would be to assume $A(x) = A$ for all x, while letting $\kappa(x)$ adjust to match observed job-finding rates according to (16). In that case, unusually low job-finding rates would be "explained" by unusually high hiring costs. In conclusion, our estimated matching efficiency series, $A(x)$, are better interpreted as matching productivities relative to hiring costs.

The calibration of human capital is based on equation (14).[18] Given a value of $W(x)$, which can be obtained by backward induction starting at the retirement age, equation (14) provides a connection between observed wages and $h(x)$, $\Theta(x) \equiv \frac{1-\phi(x)}{\phi(x)}$, and $\bar{c}(x)$. Studies by Card, Cardoso, and Kline (2016) and Isojärvi (2018) suggest that differential bargaining powers have fairly modest effects on explaining wage differentials. For this reason, we assume identical bargaining powers for all groups, and, following the literature, we further assume that the Hosios condition (Hosios, 1990) holds so that $\phi(x) = \alpha = 0.5$ and $\Theta = 1$.[19] Using this assumption and equation (20), equation (14) can be written as

$$(1 + \gamma(x))\, h(x) = 2w(x) - \beta W(x). \tag{19}$$

This expression is the basis for the reverse engineering of human capital stocks. Similar

[18] The calibration of human capital for the last period before retirement is based on equation (21) in Appendix 1.

[19] Córdoba, Isojärvi, and Li (2021) show that the Hosios condition is a sufficient condition for decentralized markets to be efficient even in the presence of learning by doing and nonparticipation. As mentioned in Footnote 14, our allocations are not fully efficient since we assume, for tractability, that unemployment is the only outside option during bargaining.

to the calibrated matching productivity series, only partial identification of human capital series is possible since wages depend on the joint term $(1 + \gamma(x)) h(x)$, human capital adjusted by its nonmarket value. This implies that a particularly low wage rate may be due to particularly low human capital of the worker, but it could also be due to a particularly low nonmarket value of the worker's human capital that weakens the worker's position during wage negotiations.

We adopt a simple and common formulation for the consumption of workers during non-employment. Following Postel-Vinay and Robin (2002), Burdett, Carrillo-Tudela, and Coles (2011), and Bowlus and Liu (2013), among others, we assume that consumption during non-employment is proportional to the human capital of the worker:

$$\begin{aligned} \bar{c}(x) &= \gamma(x) \cdot h(x) \text{ for } a < a_R, \\ \bar{c}(x_R) &= \gamma^R \cdot h_i(e, a_{R-1}) \text{ for } a \geq a_R. \end{aligned} \tag{20}$$

The first row of equation (20) presents the consumption for working-age non-employed, where $\gamma(x)$ is the wage replacement rate for the non-employed. The second row shows the consumption for the retired workers, γ^R being the pension replacement rate. This simple formulation can be justified by the fact that unemployment benefits and pensions usually depend on past earnings, and nonmarket activities also depend on the productivity of the worker.

Our benchmark calibration assumes $\gamma(x) = \gamma$ so that all wage differentials are fully attributed to human capital differentials. This choice reflects the traditional view on wages as primarily reflecting the true productivity of the workers. We calibrate γ such that the average consumption during unemployment in the model is about 40 percent of the average consumption for the employed, following Shimer (2005). The calibrated value of γ is found to be 0.35. We choose $\gamma^R = 0.33$, which implies that the average consumption during retirement is about 50 percent of the average human capital at the age of retirement. Our results are robust to different plausible values of γ^R. Given $\gamma(x)$ and observed series of wages, $w(x)$, equation (19) can be used to obtain human capital series, and equation (1) can be used to obtain y_i and $r(x)$ as $y_i = h(0, 0, i, E)$ and $r(x) = \frac{1}{e} \frac{lnh(x)}{y_i}$.

An implication of assuming $\gamma(x) = \gamma$ is that any discriminatory behavior affecting wages will not be attributed to discrimination *outside* the labor market. However, discrimination during hiring and in the workplace can be captured by the benchmark. Specifically, any discrimination in hiring would be included as part of the calibrated values of $A(x)$ and affect wages through the term $W(x)$. Discrimination in the workplace would be incorporated as part of the human capital series, particularly in the returns to experience, $r(x)$. The traditional interpretation of differences in returns to experience obtained from Blinder-Oaxaca decompositions is that they reflect some type of discrimination (Blau & Kahn, 2017). The robustness section, Section 6, considers an alternative identification approach that allows discrimination outside the labor market to affect wages. It assumes common returns to experience across groups and uses equation (19) to recover series of $\gamma(x)$ rather than series of human capital.

As we only observe average job-finding rates and average wages for every age, but not for every level of experience, we use the model's analytical averages to match the corresponding data. In practice, the data restrictions imply that we can only recover $A(x) = A_i(a, s)$ and $r(x) = r_i(a)$. Details of the calibration strategy are provided in Appendices B and C, along with the calibration algorithm. To further clarify the interpretation of the differences in job-finding rates between unemployed and nonparticipant, we calibrate the search effort of nonparticipants, $\psi_i(a)$.[20] To do that, we need an additional restriction. We assume that the general matching efficiency is equal for both unemployed and nonparticipants, $A_i(a, \bar{U}) = A_i(a, \bar{N}) = A_i(a)$, which then implies that $\psi_i(a)$ captures unexplained differences in job-finding rates between unemployed and nonparticipants for any given i and a.

4.3 Reverse-Engineering Results

4.3.1 Life-Cycle Human Capital Profiles

Figure 4 displays average, reverse-engineered human capital and returns to experience profiles as well as average wage and experience profiles over the life cycle for eight demographic groups.[21] As described earlier, human capital profiles are obtained such that the model exactly matches average life-cycle wages. Baseline, or education-related human capital levels, y_i, are depicted by the initial human capital levels at age 25, while the returns to experience, $r_i(a)$, are reflected in the human capital growth rates over the life cycle. Wedges in initial human capital levels and returns to experience could reflect differential schooling and occupational choices but also discrimination in the labor market to some extent. They could be interpreted as "occupational wedges": a representative worker in each demographic group chooses an occupation with a different level of initial skills and future human capital growth rate. For example, a worker with a lower level of education is likely predetermined to have a low initial human capital level and human capital growth rate in the future.

A partial validation of the calibrated human capital profiles is provided by the results obtained for White males, the case most studied in the literature. The calibrated average human capital profile of White males is closely connected to average wages during the life cycle until around age 55. In particular, human capital starts low, grows faster for young workers, and slows down over the life cycle in the same way as the growth of wages. Our series for White males is roughly consistent with the one obtained by other search models that also find a close association between wages and human capital (Bowlus & Liu, 2013, p. 306). The association is not perfect, however. First, wages grow faster than human capital, until around age 50, reflecting improving labor market conditions over the life cycle, such as decreasing job separation rates and increasing job-finding rates. Second, human capital does not exhibit the clear inverted-U shape of wages. The model predicts a diver-

[20]Search effort of all unemployed groups is assumed to be equal to 1.

[21]See Appendix C for the disaggregated results for skilled and unskilled groups. The findings described in this section are generally robust to the disaggregation.

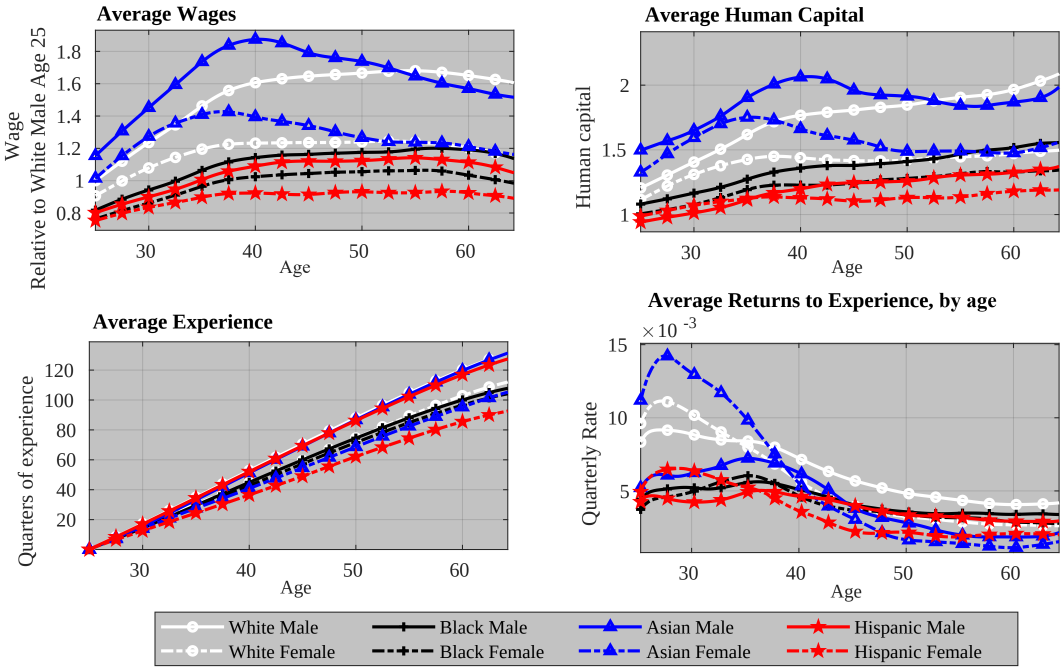


Figure 4: Average wage, human capital, experience, and returns to experience profiles over the life cycle, relative to the wage of an average 25-year-old White male.

gent path of wages and human capital after age 55, with wages falling while human capital is still increasing. The falling wages reflect the effect of a finite working life that gradually reduces the surplus of the match, and therefore wages, as a worker approaches retirement. This feature is consistent with similar life-cycle search models, such as Hairault, Cheron, and Langot (2007), Cheron, Hairault, and Langot (2013), and Menzio, Telyukova, and Visschers (2016). Rising human capital is needed to partly offset the finite-horizon effect and avoid wages falling too rapidly. The model thus implies that White males are most productive just before retirement, despite their falling wages.[22] The significant but not perfect association between wages and human capital signifies that search frictions play an important but not crucial role in wage determination. All in all, our calibrated human capital profile for White males is consistent with existing results in the literature.

Figure 4 also displays human capital estimates for other, less studied demographic groups. We find significant variation in human capital profiles along all demographic dimensions: age, skill, gender, and race. Within race, males have higher levels of human capital over the life cycle compared to females. However, there are two subperiods with markedly different evolution. Early in the life cycle and up to around age 33, the human capital of female groups grows faster than that of males, and in the case of Hispanics, females have higher human capital than males on average. Such convergence in human capital across genders is not reflected in wages, partly because of the slowly weakening female labor market outcomes as job separation rates increase. Females then face stagnat-

[22]Increasing human capital at the end of the life cycle in our model plays an analogous role to the fall in reservation productivity considered by Cheron, Hairault, and Langot (2013).

ing or declining human capital between ages 35 and 50 likely related to career breaks: as many women leave the labor market during prime working ages due to family and other reasons, the average human capital for those groups is lower. The opening gap after age 35 is due to an increasing gap in experience but also due to a decline in the returns to experience.

Within gender, we also find fairly large differences in human capital profiles for different races, and the differences increase over the life cycle. Asian males have the highest human capital until age 55, when White males take the lead. Black and Hispanic males have significantly lower human capital levels compared to Asian and White males, with Blacks having somewhat higher human capital compared to Hispanic males, although their wages are similar. Asian females have the highest human capital over the life cycle compared to other female groups, followed by White females. Again, Black and Hispanic females have fairly similar human capital levels over the life cycle, but significantly lower levels compared to Asian and White females. The racial gaps in human capital are, however, smaller for women than for men. The average experience of Black males is atypically low for males and driven by their unusually high job separation rates and low job-finding rates. Black males also have unusually low returns to experience early in the life cycle.

It is worth noting that the life cycle human capital profiles for Asians are distinct from all other groups. Their human capital starts from a significantly higher level and grows rapidly until age 35 for females and age 40 for males. However, unlike for other groups, their human capital starts *decreasing* after that. There are at least two possible explanations. First, the shape of the human capital profiles of Asians could capture cohort effects: it is possible that earlier cohorts in skilled Asian groups were choosing different occupations with very different returns to experience. This could show a relative decrease in human capital for older workers: since older workers in the data represent more heavily older cohorts, this cohort effect could explain the pattern. We study this effect by running our results for two different periods: 1989 to 2018 and 1998 to 2018. Our hypothesis is that if the cohort effect is strong, the results should be different between these two time periods, as the 1989–2018 period includes older cohorts. However, we do not find this to be the case, which implies that there are likely other explanations. Another possible reason could be that skilled Asians face relatively more obstacles in terms of promotions, for which there is some evidence. While Asians are the most educated group (50.6 percent of those aged 25 years and older have at least a bachelor's degree compared to the national average of 30.1 percent), they are the least likely group to be promoted to managerial positions, and they are not well represented in executive positions (Gee & Peck, 2017). An exclusion of Asians from the highest-paid positions could then show up as stagnating wages and human capital in the data.

4.3.2 Life-Cycle Matching Efficiency Profiles

We next present the reverse-engineered matching efficiencies, $A(x)$. Differences in matching efficiencies across labor markets reflect differences in job-finding rates that cannot be explained by the differences in fundamentals: match values and vacancy posting costs. Examples of factors that can affect $A(x)$ include geography, hiring practices, search intensity, and regulations specific to a type x. Wedges in matching efficiencies can also capture taste-based discrimination or prejudices in the labor market affecting the job-finding rates of different demographic groups. The results in this section are related to those of Barnichon and Figura (2015) and Hall and Schulhofer-Wohl (2018), who also study matching efficiency under heterogeneity and segmented markets. While they focus on aggregate business cycle properties of matching efficiencies, our focus is on life-cycle and demographic features.

Figure 5 shows the job-finding rates and the reverse-engineered matching efficiencies of the unemployed. The first thing to notice is that there exists variation in the matching efficiencies, indicating that there are differences in the job-finding rates that cannot be explained by the differences in fundamentals between demographic groups. At first glance, the calibrated efficiency profiles resemble, to a large extent, the profiles of the job-finding rates, an impression that is largely shaped by the results for Hispanic males and, to a lesser extent, Black females. These two groups exhibit the highest and lowest job-finding rates, respectively, and also end up being the ones with the highest and lowest matching efficiencies.[23] Thus, the simple cost-benefit analysis cannot fully explain these outermost job-finding rates without significant differences in matching efficiencies. A closer look at the calibrated profiles reveals, however, a more complex relationship. In particular, many of the large systematic gaps in job-finding rates do not translate into large systematic gaps in matching efficiencies. We next summarize some salient features of the calibrated matching efficiencies.

First, while job-finding rates trend downward over the life cycle for all groups, matching efficiencies are flatter for many of the groups. This is particularly clear for White males and White females, as well as for Hispanic females. In those cases, the falling job-finding rates over the life cycle are explained largely by the declining value of the match as the retirement age of workers gets closer. A strong downward trend in matching efficiency is clear for Hispanic and Asian males after ages 40–45, and less strong but clear for Black males. For these groups, age discrimination in hiring may play an important role and would show up as a decreasing matching efficiency for older workers. Second, despite their lower job-finding rates, matching efficiencies are relatively high for Hispanic females and Asian males.

Our third observation relates to gender gaps. Similar to human capital gaps, males tend to have higher matching efficiencies within race compared to females. This is especially pronounced for younger workers. Gender gaps in matching efficiency increase and then fall over the life cycle. Hispanics have the widest gender gap among races, followed by Asians, Blacks, and Whites. The gender gap for Whites is small and disappears at around

[23] A possible alternative explanation for the high job-finding rates of Hispanics would be that they have weaker outside options because of their legal status and language barriers. Although a weaker outside option could explain the particularly low wage rates of Hispanics, high matching efficiencies are still needed in the model to match the relatively high job-finding rates of Hispanics. See Section 6 for details.

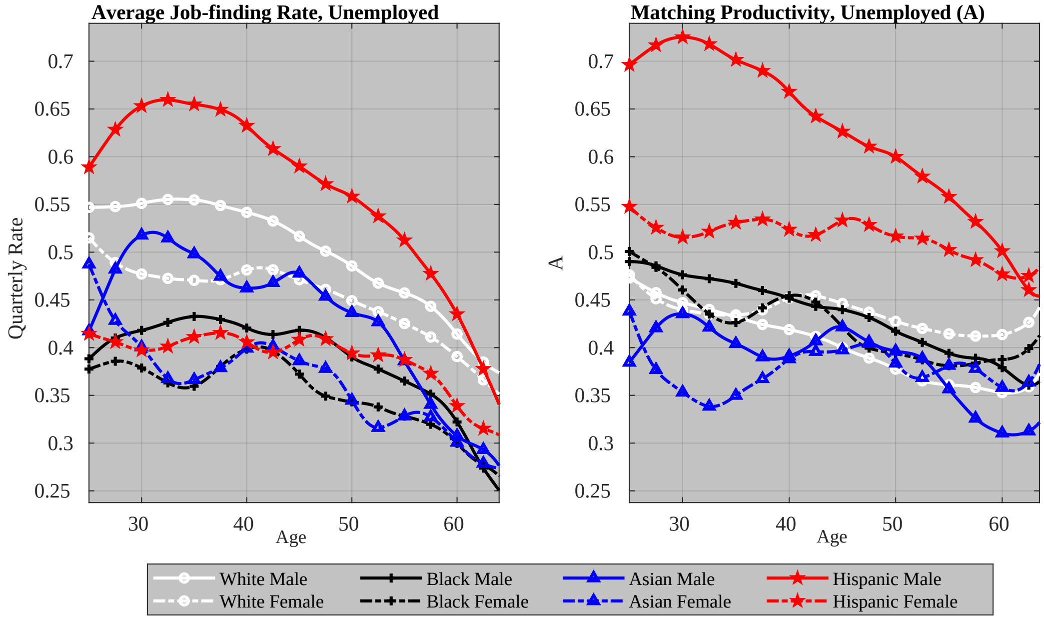


Figure 5: Average job-finding rate and matching efficiency profiles over the life cycle.

age 40. Finally, when it comes to racial differences in matching efficiency, Hispanics have the highest matching efficiency over the life cycle. Within males, Hispanics have significantly higher A compared to other male groups. They are followed by Asians, Whites, and Blacks, but the racial differences are more modest between those three groups. When it comes to females, White females have the second-highest matching efficiencies over the life cycle, while Asians and Blacks have lower but fairly similar matching efficiencies.

The calibrated matching efficiencies suggest mixed results for the potential role of taste-based discrimination during hiring. On the one hand, minority groups such as Hispanics and Asian males exhibit particularly high matching efficiencies. On the other hand, there is a persistent but narrow efficiency gap between Black and White males and a larger and persistent gap between Black and White females and between Asian and White females. As will become clear in the counterfactual exercises below, White males do not exhibit particularly high matching efficiency despite their observed high job-finding rates because of their lower separation rates and higher returns to experience. Everything else being equal, profit-maximizing firms would naturally post more vacancies for workers with lower separation rates and higher returns to experience.

We further reverse engineer the search effort of nonparticipants, $\psi_i(a)$, over the life cycle, and the detailed results are presented in Appendix C. To summarize the results, the search effort is higher for younger workers and decreases with age for most of the groups, consistent with the intuition that young workers are more actively attached to the labor market. The search effort is also typically higher for males than females and the lowest for Whites. This last result is needed for the model to account for the fact that job-finding rates, out of nonparticipation, tend to be lower for Whites even if they have lower separation rates and higher returns to experience.

5 Decomposition of the Labor Market Outcome Gaps

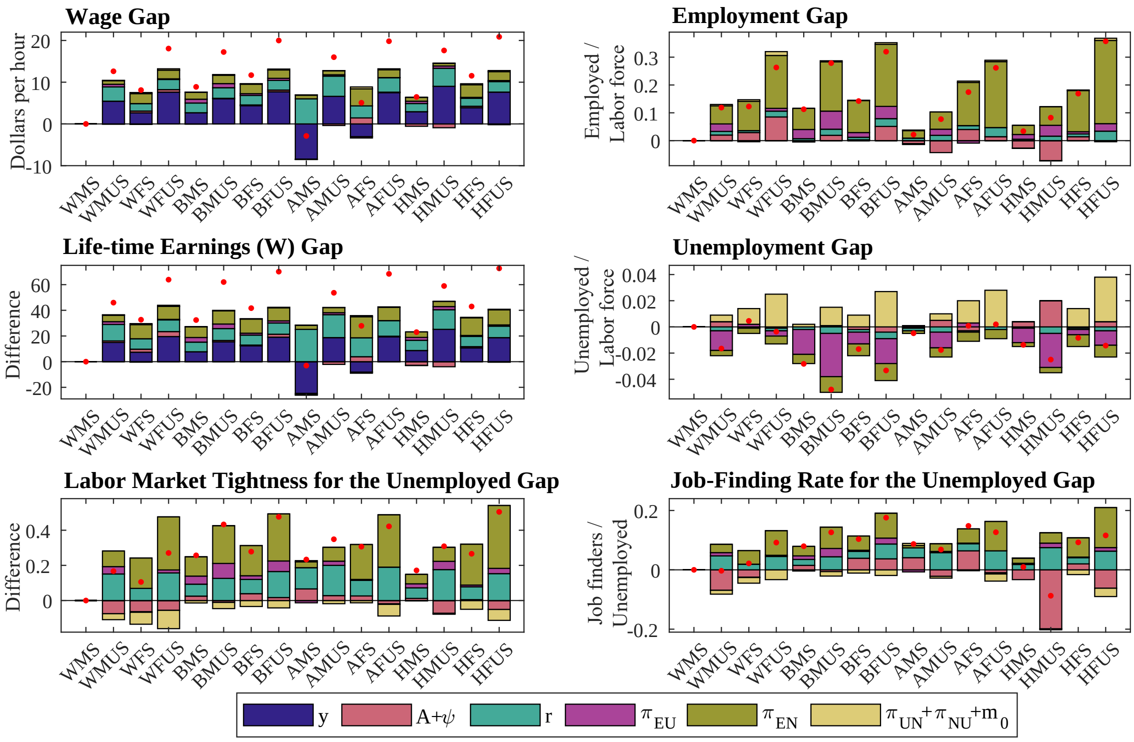
In this section, we assess the quantitative role of the recovered parametric wedges in accounting for differences in labor market outcomes as well as their macroeconomic significance. We consider four sets of counterfactuals: one that eliminates all gaps simultaneously, one that only eliminates gender gaps, one that eliminates racial gaps, and one that eliminates skill gaps. In each counterfactual, we close the wedges in exogenous variables, one by one, between the comparison group and the reference group and calculate the effect on labor market outcomes. These decompositions inform us about the relative importance of each exogenous variable in accounting for labor market disparities. Workers can differ along nine dimensions: human capital parameters ($y(x)$, $r(x)$), matching efficiencies ($A(x)$, $\psi(x)$), exogenous labor market flows ($\bar{\pi}_{EN}(x)$, $\bar{\pi}_{EU}(x)$, $\bar{\pi}_{UN}(x)$, $\bar{\pi}_{NU}(x)$), and the initial mass distribution among each employment status, s, at the beginning of the life cycle ($m_i^s(0, \underline{a})$). Aggregate impacts are calculated as weighted averages of the disaggregated impacts using each group's population share in 2018 as a weight. For more precision, we use the calibrated parameters for the skilled and unskilled groups, as reported in Appendix C, rather than just the aggregate categories reported in Section 4.[24]

We also identify the quantitative importance of statistical discrimination by running a counterfactual in which μ is set to 0. This prevents firms and workers from using group-specific job destruction rates when deciding how many vacancies to create and when negotiating wages. Firms instead use job separation rates of the corresponding reference group in the counterfactual.[25] As $A(x)$ captures unexplained differences in job-finding rates between groups, we use the counterfactual eliminating gaps in $A(x)$ to assess the potential magnitude of taste-based discrimination in explaining aggregate labor market gaps.

To deal with gaps that are close to zero, we report "absolute contributions" rather than simple contributions. To illustrate the issue, and the solution, consider the decomposition of the unemployment gap shown in the fourth panel of Figure 6. Since some of the gaps, relative to the reference group, are close to zero, and since some of the underlying explanatory factors have a positive impact while others have a negative impact on the gap, the percentage contributions of individual factors could result in figures like +150 percent, +50 percent and -100 percent. Values like these suggest the relative importance of each factor, but the exact ranking is sometimes unclear. To keep individual contributions bounded by 100 percent and adding up to 100 percent, we define the *absolute contribution* as the value of the raw contribution relative to the sum of the raw contributions in absolute values. In the example above, the absolute contributions are 150/300=50 percent, 50/300=16.6 percent and -100/300=-33.3 percent. The absolute values of these contributions add up to 100 percent. This methodology is helpful, as it indicates that the first factor is the main

[24]The results are qualitatively similar if only aggregate categories, as described in Section 4, are used. Quantitatively, the results reported in this section based on the more disaggregated categories provide a larger role for initial human capital levels and a lesser role for job separation rates.

[25]The exercise is different from the one carried out for the no statistical discrimination model (NSD), described in Section 6. This section uses the calibrated parameters of the SD model ($\mu = 1$) to assess what happens if μ is set to zero so that firms cannot statistically discriminate based on job separation probabilities.



Notes: The dots in the graphs demonstrate the observed gaps. Each bar represents a demographic group. The first letter of each acronym denotes race/ethnicity (A=Asian, B=Black, H=Hispanic, W=White), the second letter gender (M=Male, F=Female), and the third skill level (US=Unskilled, S=Skilled).

Figure 6: Decomposition of the skilled White male premium.

determinant of the gap, while the third factor is the second-most important determinant, although its contribution is negative. The proposed methodology has a bigger impact on how accounting results are reported for variables such as unemployment, tightness, and job-finding rates, but only a minor impact on other variables such as wages, employment rate, and lifetime earnings. For completeness, the detailed tables included in Appendix D also report the raw values.

5.1 Decomposition of Skilled White Male Premium

Our first counterfactual exercise uses skilled White males as the reference group. We equate, one by one, all the parameters of other groups to the values of the reference group within age and assess the individual impact of each parameter in generating labor market gaps. This exercise eliminates skill, gender, and racial gaps simultaneously. It also provides an upper bound for the potential aggregate gains of eliminating all types of labor market disparities, frictions, and discrimination. Figure 6 shows the decomposition results between the reference group and each remaining individual demographic group and for six different labor market gaps. The dots in the graphs demonstrate the observed gaps. Tables 2 and 3 report the corresponding aggregate decomposition results for selected labor market variables. The first column shows the decomposition of the skilled White male premium.

Consider first the determinants of wage gaps. Figure 6 and Table 2 show that wage gaps arise primarily from the differences in human capital parameters, $y(x)$ and $r(x)$. Differences in these two parameters account for around three-fourths of the average explained wage gap, with differences in initial human capital accounting for around half of the explained wage gap. Search frictions account for the remaining one-fourth of the explained wage gap. This split is similar to other findings in the search literature. For example, Bowlus and Liu (2013, p. 305) find that "human capital accumulation accounts for 50 percent of total earnings growth, job search accounts for 20 percent, and the remaining 30 percent is due to the interactions of the two." Our corresponding decomposition, considering that the explained gap is 78 percent of the actual wage gap, are 47 percent, 23 percent, and 27 percent, respectively (see Table D3.1 in Appendix D). The similarity of the split is perhaps reassuring given that Bowlus and Liu (2013) focus on wage growth of White males rather than wage dispersion among demographic groups, use a different human capital mechanism (Ben-Porath) rather than learning by doing, and employ National Longitudinal Survey of Youth 1979 data rather than CPS data. The key role of human capital variables reflects the fact that the reference group, skilled White males, generally displays higher education levels and higher average returns to experience compared to other demographic groups, except Asian groups, which exhibit significantly larger initial human capital but also significantly lower average returns to experience than the reference group. We focus our comments on the decomposition of the explained components, as the explained components consist of 80 percent of the total gaps (see Table D3.1 in Appendix D for details).

The third-most important wedge accounting for the explained wage gaps is in the job destruction rate to nonparticipation ($\bar{\pi}_{EN}$). This wedge alone accounts for around 19 percent of the explained wage gap. Part of this effect comes from the fact that a high $\bar{\pi}_{EN}$ is directly related to career interruptions, lower experience, and slower accumulation of human capital. Surprisingly, the majority of the effect comes from the fact that a high $\bar{\pi}_{EN}$ weakens a worker's outside option in wage bargaining, leading to a lower wage. We will return to this result when analyzing the role of statistical discrimination below.

Consider next the determinants of other labor market outcomes. Gaps in employment rates reported in Table 3 are largely driven by the wedges in job separation rates, mainly in $\bar{\pi}_{EN}$, although wedges in $\bar{\pi}_{EU}$ also play a significant role. High separation rates directly lead to lower employment but they are also the major determinants of the differences in the probability of moving back to employment, as seen when looking at the decomposition for the job-finding rates of the unemployed $\bar{\pi}_{UE}$. Returns to experience, $r(x)$, have a large effect on job-finding rates, as they determine the expected long-term value of a match. Notice that while differences in initial human capital are the key determinant of the wage gaps, they play no role in explaining gaps in other labor variables such as employment or job-finding rates. The reason is that, as discussed in Section 3, the model is scale-invariant in human capital levels.

Interestingly, equating the matching efficiencies $A(x)$ of all groups to that of the ref-

Table 2: Decomposition of the wage and lifetime earnings gaps.

Panel A. Absolute contributions, wages

	All gaps	Skill gaps	Gender gaps	Race gaps
Human capital				
Initial human capital (y)	46.9%	59.8%	38.4%	24.2%
Returns to experience (r)	26.9%	23.5%	15.4%	36.5%
Total	73.8%	83.3%	53.8%	60.7%
Search frictions				
Matching efficiency (A)	-0.7%	-2.1%	4.7%	0.2%
Search effort, nonparticipants (ψ)	2.2%	1.7%	5.2%	-6.7%
Separation rates (d)				
To unemployment (π_{EU})	2.8%	3.9%	-3.3%	8.5%
To nonparticipation (π_{EN})	18.7%	8.2%	29.4%	21.9%
Total	23.0%	11.7%	36.0%	23.9%
Statistical discrimination	15.1%	9.3%	16.0%	22.6%

Panel B. Absolute contributions, lifetime earnings W

	All gaps	Skill gaps	Gender gaps	Race gaps
Human capital				
Initial human capital (y)	35.4%	48.8%	27.6%	16.5%
Returns to experience (r)	29.7%	25.2%	18.2%	31.4%
Total	65.1%	74.0%	45.8%	47.9%
Search frictions				
Matching efficiency (A)	-0.9%	-2.8%	4.2%	1.3%
Search effort, nonparticipants (ψ)	4.0%	4.9%	7.7%	-14.0%
Separation rates (d)				
To unemployment (π_{EU})	2.9%	4.3%	-3.3%	8.4%
To nonparticipation (π_{EN})	25.7%	13.1%	36.2%	26.6%
Total	31.9%	19.5%	44.8%	22.3%
Statistical discrimination	24.0%	15.2%	25.3%	30.7%

Notes: The role of statistical discrimination is obtained by setting μ=0, which implies that firms cannot observe the true d for each demographic group when posting vacancies and bargaining over wages. The total contribution of d can be divided into two parts: statistical discrimination and direct effect, contribution of d = statistical discrimination + direct effect.

Table 3: Decomposition of the employment and job-finding rate gaps.

Panel A. Absolute contributions, employment

	All gaps	Skill gaps	Gender gaps	Race gaps
Human capital				
Initial human capital (y)	0.0%	0.0%	0.0%	0.0%
Returns to experience (r)	7.4%	8.5%	2.7%	4.5%
Total	7.4%	8.5%	2.7%	4.5%
Search frictions				
Matching efficiency (A)	-3.2%	-10.2%	10.8%	-3.1%
Search effort, nonparticipants (ψ)	12.6%	17.7%	14.5%	-29.3%
Separation rates (d)				
To unemployment (π_{EU})	8.2%	13.5%	-6.2%	13.3%
To nonparticipation (π_{EN})	64.0%	47.0%	59.0%	46.7%
Total	81.6%	68.0%	78.1%	27.6%
Statistical discrimination	14.6%	13.4%	10.2%	13.7%

Panel B. Absolute contributions, job-finding rate, unemployed

	All gaps	Skill gaps	Gender gaps	Race gaps
Human capital				
Initial human capital (y)	0.0%	0.0%	0.0%	0.0%
Returns to experience (r)	26.2%	25.9%	8.9%	17.4%
Total	26.2%	25.9%	8.9%	17.4%
Search frictions				
Matching efficiency (A)	-14.6%	-30.4%	29.6%	-22.2%
Search effort, nonparticipants (ψ)	-6.0%	-6.0%	-8.0%	13.5%
Separation rates (d)				
To unemployment (π_{EU})	4.4%	7.0%	-3.9%	9.2%
To nonparticipation (π_{EN})	37.7%	23.6%	36.1%	28.4%
Total	21.5%	-5.8%	53.8%	28.9%
Statistical discrimination	46.7%	34.2%	32.6%	40.7%

Notes: The role of statistical discrimination is obtained by setting μ=0, which implies that firms cannot observe the true d for each demographic group when posting vacancies and bargaining over wages. The total contribution of d can be divided into two parts: statistical discrimination and direct effect, contribution of d = statistical discrimination + direct effect.

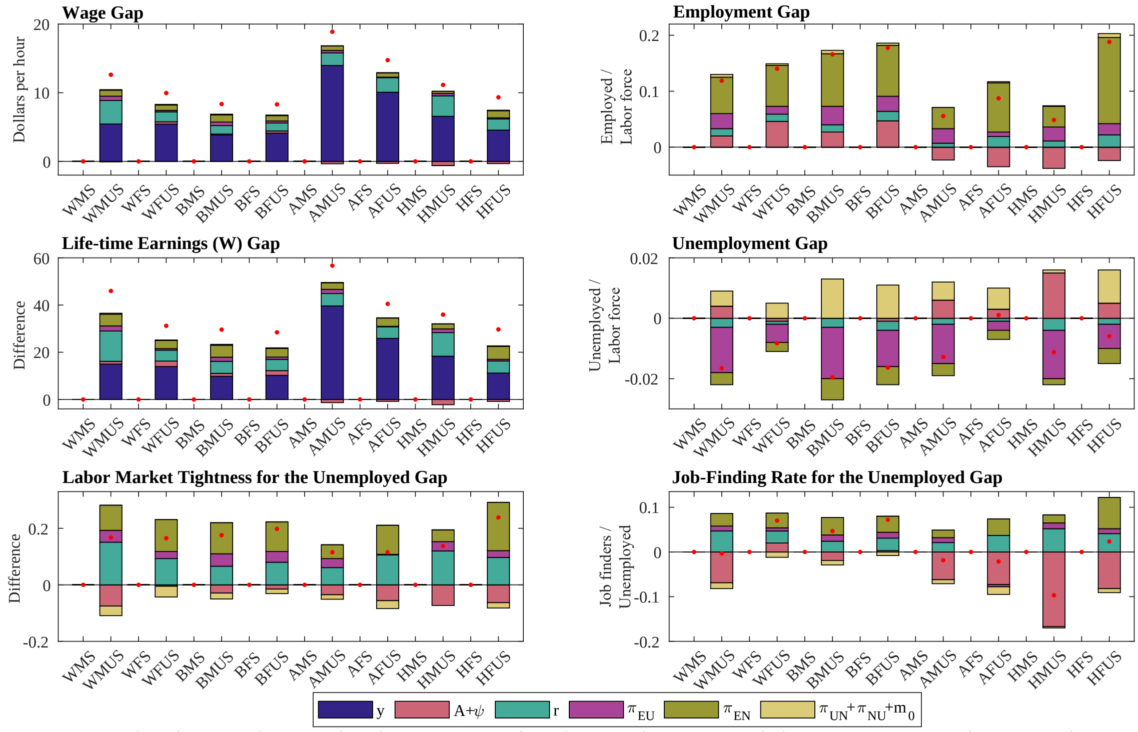
erence group would further increase most labor market gaps. The reason is that the calibrated matching efficiency for skilled White males is more on the average level, while some groups, such as Hispanics and the unskilled, tend to exhibit higher matching efficiencies. The role of taste-based discrimination in hiring thus seems limited when considering the unemployed.

The key labor market outcome of the model is the average lifetime earnings of workers, $W(x)$, as defined by equation (9). This average welfare measure takes into account all the wage and employment information of a worker.[26] The decomposition results for the average W reported in Table 2 follow somewhat closely the decomposition results for wages, emphasizing the roles of human capital parameters and $\bar{\pi}_{EN}$. However, as W depends closely on both life-cycle wages and employment, the role of $\bar{\pi}_{EN}$ is greater and the role of y_i is smaller in generating these gaps compared to the wage gap decomposition. We find that, from the point of view of average lifetime earnings, W, human capital differences account for 65 percent of the total earnings disparities, while search frictions account for about 32 percent.

Finally, we investigate the role of statistical discrimination in generating the gaps. For this purpose, we set $\mu = 0$, which equates the separation rates of all groups to the reference group, but only for a job posting and wage bargaining decisions. Actual separation rates are still used when calculating job flows into unemployment and nonparticipation— what we call the direct channel. We find that statistical discrimination explains the majority of the impact that comes through job separation rates when looking at the wage, job-finding rate, and earnings gaps. Around 70 percent of the role of $\bar{\pi}_{EU}$ and $\bar{\pi}_{EN}$ in generating wage gaps arises from firms' differential treatment of groups based on their job destruction rates accounting for 15 percent of the total wage gaps, while the rest is coming through the direct channel. According to the model, higher job destruction probabilities lower a worker's outside option in the wage negotiation, leading to lower wages. Around half of the gaps in job-finding rates can be explained by statistical discrimination, according to the model. Firms post fewer vacancies to workers with higher job destruction rates. Around 24 percent of the overall welfare gaps over the life cycle are coming through this discrimination channel. The contribution of statistical discrimination is smaller when looking at the employment outcome, as this outcome depends closely on the direct channel affecting the employment masses. The rest of the impact is coming through the discrimination channel affecting a worker's job-finding rate.

In contrast to the role of taste-based discrimination, we find a potentially significant role for statistical discrimination in explaining the aggregate outcome gaps between different skill groups, genders, and races. According to Tables 2 and 3, statistical discrimination alone can explain around 15 percent of both wage and employment gaps and around half the gaps in job-finding rates. The impacts on life-cycle welfare gaps are also large, at around 24 percent.

[26]Since a period in the model is a quarter, W is measured in quarters of earnings.



Notes: The dots in the graphs demonstrate the observed gaps. Each bar represents a demographic group. The first letter of each acronym denotes race/ethnicity (A=Asian, B=Black, H=Hispanic, W=White), the second letter gender (M=Male, F=Female), and the third skill level (US=Unskilled, S=Skilled).

Figure 7: Decomposition of skill gaps.

5.2 Decomposition of Skill Gaps and Skill Premium

Our second exercise decomposes the sources of skill gaps, or skill premium. These are gaps in labor market outcomes between skilled and unskilled individuals of the same gender, race, and age. As shown in Table 1, the outcome gap between the skilled and unskilled is the largest component of the total gaps. Skill gaps represent 49 percent of the total gains of eliminating all gaps in wages and 42 percent and 45 percent of the overall explained gaps in lifetime earnings and employment, respectively.

The decomposition exercise uses skilled individuals of the same gender, race, and age as the reference group, and the results are shown in Figure 7 and Tables 2 and 3. As expected, the two human capital variables, initial human capital and returns to experience, account for most of the skill premium in wages and lifetime earnings (83 percent and 74 percent, respectively) and less of the corresponding premiums in employment and job-finding rates (9 percent and 26 percent, respectively). Initial human capital is the dominant factor, accounting for around 60 percent of the skill wage premium and for around half of the premium in lifetime earnings.

While a predominant share of the skill premium can be explained by human capital differences, an important share of the skill premiums are explained by search frictions—in particular, by wedges in separation rates. The lower separation rates of skilled workers account for 12 percent, 61 percent, and 17 percent of the premiums in wages, employment, and lifetime earnings, respectively. According to the model, statistical discrimination accounts for between 9 and 15 percent of the skill premiums in wages, employment, and lifetime earnings, and 34 percent of the skill premiums in job-finding rates. While statistical discrimination is moderately important in generating skill premiums, the higher average $A(x)$ of the unskilled improves the labor market outcomes of the unskilled and decreases skill gaps limiting the potential role of taste-based discrimination in generating the skill premiums.

These accounting results indicate that higher human capital—the ability of a worker to generate output—is the main reason why skilled workers enjoy labor market premiums. But it is not the only reason. Skill premiums also reflect lower separation rates and statistical discrimination that favor skilled workers.

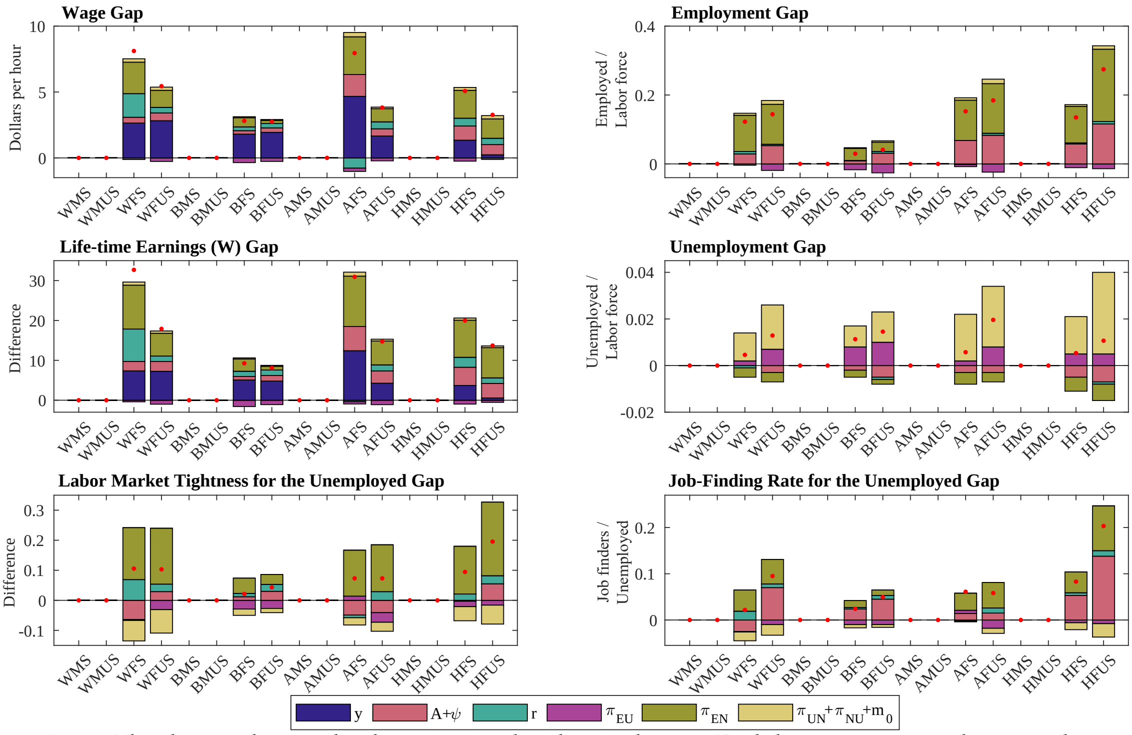
5.3 Decomposition of Gender Gaps and Male Premium

The gender gap is the second-largest component of the total gaps. According to Table 1, it accounts for 27 percent, 29 percent, and 49 percent of the overall explained gaps in wages, lifetime earnings, and employment, respectively. The decomposition results, shown in Figure 8 and Tables 2 and 3, suggest fairly equal roles for human capital and search frictions in explaining gender gaps in wages (54 percent and 36 percent) and lifetime earnings (46 percent and 45 percent), but a minimal role for human capital variables in explaining the significant gender gaps in employment and job-finding rates. The gender gap in job separation rates to nonparticipation ($\bar{\pi}_{EN}$) is either the main or a major factor explaining gender gaps in outcomes, and the majority of the impact enters through statistical discrimination. The respective contributions of $\bar{\pi}_{EN}$ and statistical discrimination are 29 percent and 16 percent for wage gaps, 36 percent and 25 percent for life-time earnings gaps, 59 percent and 10 percent for employment gaps, and 36 percent and 32 percent for job-finding rates of the unemployed. High job separation rates of females lead to significantly weaker labor market outcomes, reflected particularly in job-finding and employment rates.

Taste-based discrimination can potentially explain a small share of male premiums in outcomes, and the role of taste-based discrimination is the largest in explaining gender gaps compared to the other gaps. Taste-based discrimination can potentially explain up to 4 to 5 percent of the gaps in wages and lifetime earnings, 11 percent of the employment gaps, and almost 30 percent of the gaps in job-finding rates. When looking at Figure 8, the role of $A(x)$ is particularly large for unskilled female groups.

5.4 Decomposition of Racial Gaps and White Premium

The racial gaps are the third largest of all gaps. According to Table 1, they account for around 18 to 20 percent of the overall gaps in wages, lifetime earnings, and employment rates. The decomposition results, shown in Figure 9 and Tables 2 and 3, suggest a strong role for human capital differentials, particularly in returns to experience and job separation rates in explaining racial gaps. Human capital deviations explain, respectively, 61 percent and 48 percent of the wage and lifetime earnings gaps and 5 percent and 17 percent of the



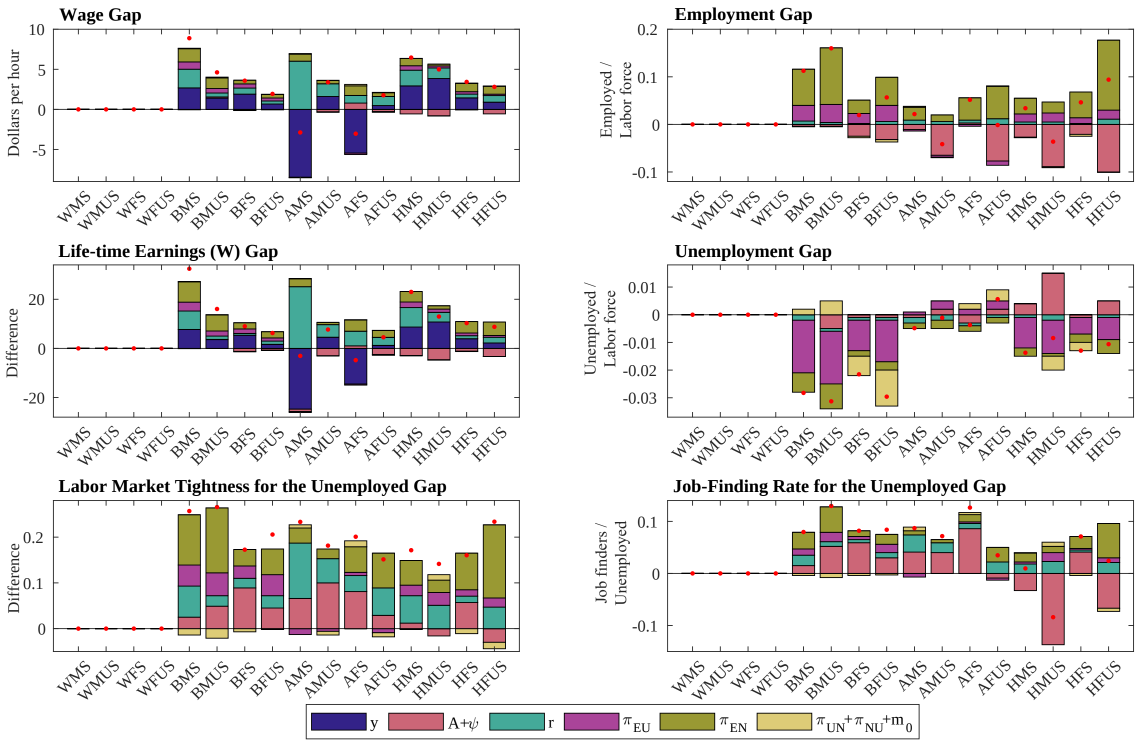
Notes: The dots in the graphs demonstrate the observed gaps. Each bar represents a demographic group. The first letter of each acronym denotes race/ethnicity (A=Asian, B=Black, H=Hispanic, W=White), the second letter gender (M=Male, F=Female), and the third skill level (US=Unskilled, S=Skilled).

Figure 8: Decomposition of gender gaps.

racial gaps in employment and job-finding rates of the unemployed. Wedges in separation rates and statistical discrimination explain, respectively, 30 percent and 23 percent of the racial wage gap, 35 percent and 31 percent of the racial lifetime earnings gap, 60 percent and 14 percent of the racial employment gap, and 38 percent and 41 percent of the gap in the job-findings rate of the unemployed.

These aggregate results hide some important differences between racial groups. As shown in Figure 9, a lower matching efficiency is an important contributor to the lower job-finding rate of the unemployed and other gaps in employment variables, particularly for unskilled Black males and skilled Asian females. The decomposition thus suggests that prejudice in hiring may be an important determinant of employment gaps for these groups. However, Hispanic groups, except for skilled Hispanic females and unskilled Asian females, exhibit particularly high matching efficiencies relative to the comparison group—an average White worker of the same age, gender, and skill. These results suggest reverse-prejudice, as employers may prefer certain minority groups for certain tasks. The overall potential effect of prejudice in hiring is relatively secondary according to our decomposition.

Bertrand and Mullainathan (2004) provide compelling evidence that race matters for hiring decisions. In their field experiment, job applicants with White-sounding names received around 50 percent more callbacks for interviews compared to otherwise similar candidates with Black-sounding names. What could be the sources of this difference? Our



Notes: The dots in the graphs demonstrate the observed gaps. Each bar represents a demographic group. The first letter of each acronym denotes race/ethnicity (A=Asian, B=Black, H=Hispanic, W=White), the second letter gender (M=Male, F=Female), and the third skill level (US=Unskilled, S=Skilled).

Figure 9: Decomposition of race gaps.

exercise sheds some light. According to our model, there are three reasons why some individuals are more employable than others: (i) higher human capital, (ii) prejudice in hiring, and (iii) statistical discrimination. Our quantitative exercise suggests that human capital differences—particularly in returns to experience—and statistical discrimination explains most of the gap. Prejudice in hiring plays a secondary role, on average, but is potentially important for certain groups. For example, our disaggregated results show that prejudice can explain up to 38 percent of the lower job-finding rate of unskilled Black males relative to unskilled White males.

6 Robustness Checks

This section provides further support to the use of the benchmark model by considering two alternative calibrations of the model. The first alternative precludes any statistical discrimination from occurring, while the second alternative allows workers' outside options—the nonmarket compensations—to vary across demographic groups enough for the model to match the observed wage gaps. We find that these alternative formulations are problematic. We have performed further robustness checks not reported here. We find that our main results are robust to the following alternatives: (i) different periods of analysis (1976 to 1980, 2003 to 2007, and 2014 to 2018), and (ii) exclusion of part-time workers

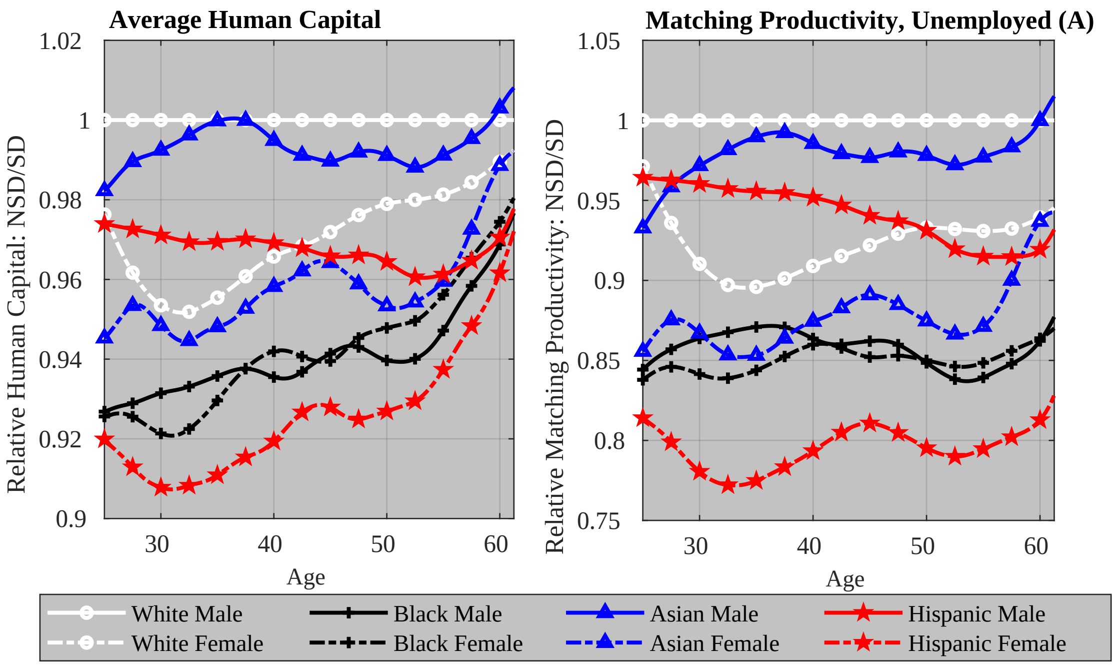


Figure 10: Human capital profiles: No statistical discrimination (NSD, $\mu = 0$) relative to statistical discrimination (SD, $\mu = 1$).

from the data sample.

6.1 No Statistical Discrimination

The benchmark model assumes $\mu = 1$, or full statistical discrimination (SD). In this section, we report results for an alternative calibration strategy with no statistical discrimination (NSD), where μ is set to be 0. This calibration strategy implies that firms are not able to statistically discriminate against workers based on group-specific job separation probabilities, $\bar{\pi}_{EN}$ and $\bar{\pi}_{EU}$. Instead, the calibration assumes that firms and workers only observe a common set of job separation rates, affected only by skill, age, and experience, but not by demographic indicators. For convenience, we choose job separation rates of White males as the common rates mainly because White males are the reference group utilized in other parts of the paper. The results in this section are robust to selecting other natural reference groups, such as population averages by age, experience, and skill.[27]

Figure 10 shows life-cycle human capital profiles and matching productivities of the NSD model relative to the SD model. A salient feature of these graphs is that the NSD model requires significantly lower human capital stocks of demographic groups, relative to White males, and lower matching efficiencies than the SD model. The required percentage drop in matching efficiencies is larger and more persistent over the life-cycle than the required drop in human capital. The large drop in matching efficiencies of all groups relative to White males suggests that reducing the role of statistical discrimination by setting

[27]Using average probabilities would be a more transparent exercise because it would be a mean-preserving change in destruction rates.

$\mu = 0$ increases the potential role of taste-based discrimination (TBD). In particular, the SD model suggests a relatively small potential role for TBD when it comes to gender and racial discrimination since matching efficiencies are only slightly lower for White females and Black males relative to White males. As the NSD model requires significantly lower matching efficiencies for these two groups, the NSD model suggests a larger potential role for TBD.

The direct effect of eliminating statistical discrimination is an increase in the value of matches for groups with higher break probabilities than White males, such as women and Black males, which increases job posting and improves job-finding rates for those groups. To counteract this effect and thus match the observed job-finding rates, the NSD model requires lower matching efficiencies for those groups. Eliminating SD would also tend to increase wages of those same groups since their match surpluses increase when separation rates fall to equate to the rates of White males. To offset this effect and thus match observed wages, the NSD model requires lower human capital stocks for those groups. Lower human capital partly reduces match surpluses and discourages job posting, but the direct effect of lower separation rates dominates, making it necessary for the NSD model to lower matching efficiencies significantly.

These exercises show the difficulties that a pure human capital model has to jointly explain the evidence on wages and job-finding rates. In other words, a model that is free of any type of discrimination in the labor market, beyond what is embodied in the human capital of the worker, would have difficulties matching the data. The results also highlight the importance of utilizing a general equilibrium model rather than a partial equilibrium one.

Finally, Figure 11 shows the labor market tightness rates for different groups relative to the rates of White males for the SD and NSD models. Tightness rates are closer to each other between different groups in the NSD model since firms cannot treat workers differently, or distinguish among workers, based on their match break probabilities. The average labor market tightness rate of White males is 1.12 times higher than the rate of Black males in the NSD model. This small gap generated by the NSD model is problematic since the evidence suggests a larger gap in the number of vacancies per unemployed worker. As mentioned earlier, Bertrand and Mullainathan (2004) find that Whites receive 50 percent more callbacks per application than Blacks. This also suggests a 50 percent higher effective vacancy posting rate for Whites compared to Blacks. The NSD model, which turns out to require significant TBD to match the data, does not produce nearly enough gap in the vacancy rates. In contrast, the SD model generates a White-Black vacancy posting ratio of 1.5, consistent with the findings of Bertrand and Mullainathan (2004). For this reason, we choose the SD model as the benchmark model.

6.2 Calibrated Outside Options

The calibration of the human capital trajectories in the benchmark model using equation (19) assumes a common replacement rate, $\gamma(x)$, for all groups. We now report results for

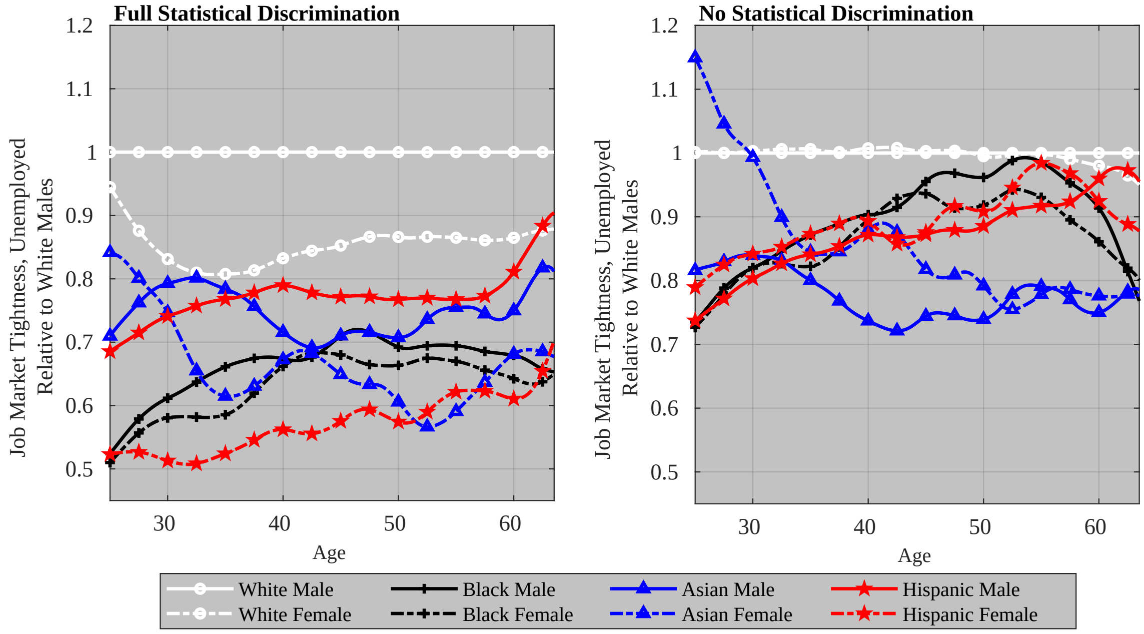


Figure 11: Labor market tightness rates for the average unemployed individuals of each demographic group relative to the average unemployed White males for the statistical discrimination model ($\mu = 1$) and the no statistical discrimination model ($\mu = 0$).

an alternative calibration that assumes a common human capital function for all groups, and uses (19) to recover group-specific series of $\gamma(x)$. The nonmarket value of human capital is then given by $\gamma(x) \cdot h(x)$, a value that allows the model to match the observed wage rates. The common human capital function used is the one calibrated for White males in the benchmark model. The function allows the initial human capital and the returns to experience to depend on the skill level.

Figure 12 shows the calibrated series of $\gamma(x)$ for various groups. The limitations of a calibration that relies on differential outside options as a way to explain wage differentials are immediately clear. The most salient limitation is that it would require the human capital of most groups to have a zero or negative value outside the labor market for a significant part of the life cycle. For example, every female group would be required to have a negative outside option by ages 35 to 40. Two other questionable implications are that (i) White males would have lower entering levels of human capital than all other groups, and (ii) White and Asian females would have an increasingly better outside option than White males early over the life cycle.

7 Relation to the Literature

Our paper relates to the large and active literature on the labor market disparities between gender and race and, more specifically, to the literature on labor market discrimination (see literature reviews in Lang and Lehmann (2012) and Blau and Kahn (2017)) and on the impacts of career breaks on labor market outcomes. The literature on discrimination using dynamic, structural approaches is fairly limited. The closest paper to ours is Gayle

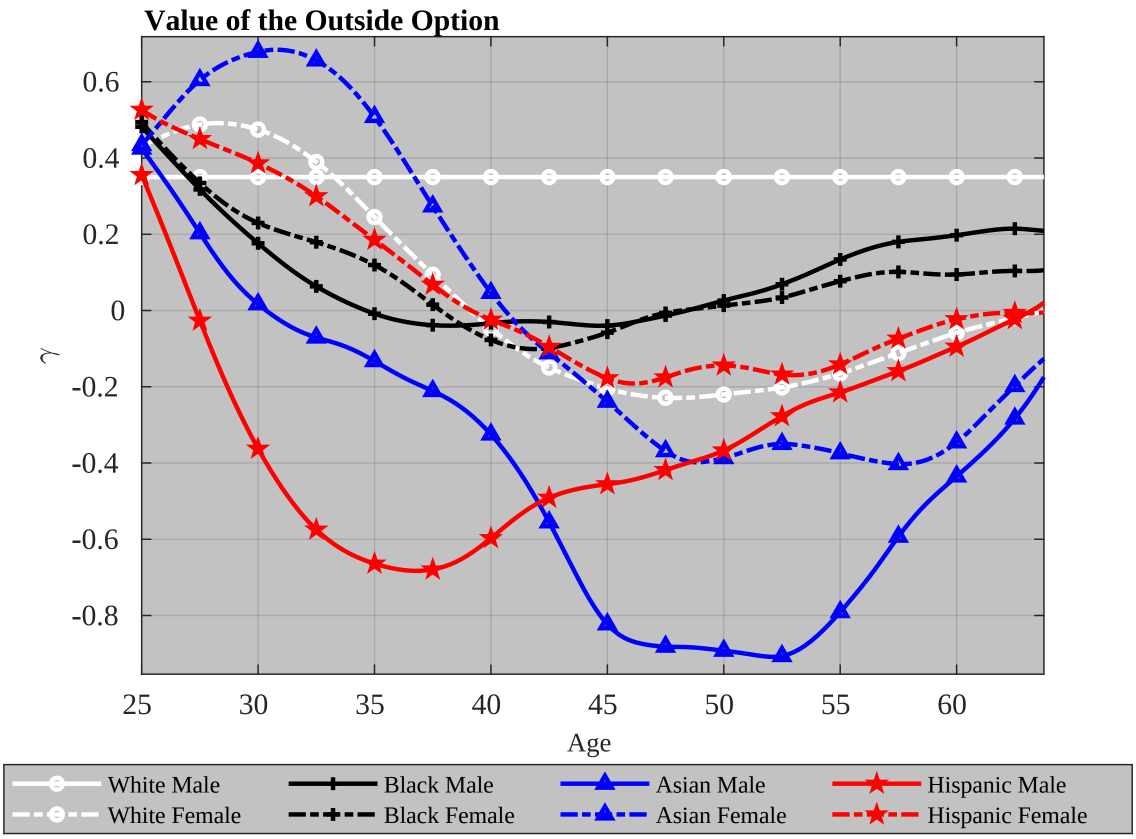


Figure 12: Value of the outside option (as a proportion of human capital) required to explain wage gaps.

and Golan (2012), who study gender discrimination and a gender wage gap by building a dynamic general equilibrium model. They find that the difference in labor market experience is the most important channel to explain the gender wage gap over the life cycle, and statistical discrimination can also explain a significant fraction of the gap. Our paper differs from theirs as we not only study the gender wage gap and discrimination, but a wider group of people. Also, we study specifically labor markets with frictions to be able to study simultaneously not only wage disparities, but also disparities in other labor market outcomes. There exists a very recent literature on identifying the causal impacts of parenthood on gender wage gaps (Angelov, Johansson, & Lindahl, 2016; Chung et al., 2017; Kleven, Landais, & Sogaard, 2019; Lundborg, Plug, & Rasmussen, 2017), and the results show consistently large and long-term impacts of parenthood on the increase in the wage gaps. More generally, there is a literature on the impact of unemployment spells on earnings. For example, Guvenen et al. (2017) found that spending one year or more out of work caused long-term losses of earnings for U.S. male workers compared to workers who stayed employed. Our paper builds on these empirical findings by modeling the relation between non-employment periods and human capital growth, and then uses the general equilibrium model to assess how a large fraction of the negative impact of the nonworking periods is arising from the discriminatory behavior of the firms.

Our theory relates to the literature on search models with human capital growth. There are earlier papers that study human capital and wage growth in search frameworks. The literature usually studies the role of human capital investment (either general or firm-specific) versus on-the-job search on wage growth. Flinn, Gemici, and Laufer (2017) study how firms and workers choose to invest in general and firm-specific human capital in a partial and general equilibrium search model, and how much of the workers' wage growth can be explained by investment in human capital versus searching for new, more productive employment opportunities. They link their results with the Mincer equation and find decreasing returns to investment in both types of human capital. Burdett, Carrillo-Tudela, and Coles (2011) also build a search model with general human capital accumulation and on-the-job search to investigate the role of each of these channels in human capital growth in the steady-state, but in their model, general human capital accumulates through learning by doing. They also connect their results with the Mincer equation to see if their model generates a reasonable connection with Mincer literature. However, they assume constant returns to experience, which differs from typical decreasing returns of experience in Mincer equations. Bagger et al. (2014) build a model along the same lines as Burdett, Carrillo-Tudela, and Coles (2011) but allow for an employee and an employer heterogeneity and productivity shocks, and they estimate the life-cycle wage growth patterns. Our paper also assumes human capital accumulation through learning by doing, but the main difference in our framework is that we also require our model to generate realistic employment, unemployment, and nonparticipation outcomes over the life cycle, in addition to wage outcomes. These other labor market outcomes are tightly linked with the wage outcomes through human capital accumulation and the wage bargaining between a worker and a firm. We also study quantitatively how well our framework can explain race and gender differences in all these labor market outcomes.

This paper also combines the literature on wage gaps with the growing literature on transition flows and their importance on unemployment and participation rates of workers (Choi, Janiak, & Villena-Roldan, 2014; Elsby, Hobijn, & Sahin, 2015; Kroft & Notowidigdo, 2016; Menzio, Telyukova, & Visschers, 2016) by studying how much gender and race differences in flow probabilities can explain differences in wage growth patterns and other labor market outcomes. This paper also relates to the literature on finite life-cycle search models (Cheron, Hairault, & Langot, 2013; Esteban-Pretel & Fujimoto, 2014; Fujimoto, 2013; Hairault, Cheron, & Langot, 2007; Bowlus & Liu, 2013, Menzio, Telyukova, & Visschers, 2016) by studying wage growth and the gender and race wage gaps in a finite life-cycle environment with human capital growth due to experience. Finally, Rauh and Valladares-Esteban (2018) study the wage and employment gaps between Black and White males in a model with endogenous human capital and exogenous separation rates. They find a similar role for separation rates as we do. Our focus is more comprehensive, and unemployment rates are endogenous in our environment, which allows us to discuss issues of statistical and taste-based discrimination.

8 Concluding Comments

The U.S. labor market is becoming increasingly diverse. At the same time, there are persistent differences in labor market outcomes, such as wages or unemployment rates, between demographic groups. This paper sought to understand the sources of unequal labor market outcomes through the lens of the canonical labor market model: the Diamond-Mortensen-Pissarides (DMP) model. We introduced standard elements into the model to make it amenable for our exercise: (i) human capital accumulates through learning by doing; (ii) workers can be nonparticipants, in addition to employed or unemployed; and (iii) labor markets are segmented.

We reverse engineered the wedges needed for the model to exactly match the observed series of wages and job-finding rates over the life cycle for a comprehensive set of demographic groups. We argue that these wedges provide useful guidance about the underlying sources of labor market disparities and for future research. We selected the DMP model for two main reasons. First, there are persistent differences in the unemployment rates between demographic groups. The DMP model is the canonical model of unemployment and therefore the natural candidate for our accounting exercise. Second, the DMP model provides a unified explanation for the main labor market variables, such as wages, employment, unemployment, and labor market participation, all of which vary systematically between demographic groups.

We found that wedges in three sets of parameters are responsible for most of the labor market disparities: gaps in initial human capital, returns to experience, and the separation rate to nonparticipation. The importance of each of these wedges varies depending on the specific gap, but the influence of each is notable whether we look at skill, gender, or racial gaps. While human capital wedges are the most important factors explaining the gaps in wages, wedges in parameters determining the long-term value of the match, returns to experience, and job separation rates can explain the majority of gaps in job-finding rates. We also found that a major fraction of the impact through job separation rates comes through the discrimination channel, emphasizing the role of statistical discrimination in generating labor market gaps. Wedges in matching efficiencies turned out to be quantitatively secondary. While we found quite a large variation in matching efficiencies between individual groups, some minority groups do better compared to the baseline groups while some do worse, and at the aggregate level those effects cancel out. This result suggests that taste-based discrimination in hiring is likely not a major explanatory variable of labor market gaps.

Bertrand and Mullainathan (2004) provide compelling evidence that race matters for hiring decisions. Everything else the same, Whites received around 50 percent more callbacks for interviews compared to Blacks in their field experiment. Our findings indicate that this is most likely because of statistical discrimination: employers infer that the long-term value of the match with a Black workers is lower, leading them to discriminate against Blacks in hiring even if they are initially exactly the same as White workers. Taste-based discrimination in hiring seems to be of secondary importance.

Our results about the importance of statistical discrimination are consistent with a large body of empirical literature (see, for example, Agan and Starr (2017), Altonji and Pierret (2001), Ayres and Siegelman (1995), Bohren et al. (2019), List (2004), and Zussman (2013)) that find evidence on discrimination in various markets, and that the discrimination is statistical in nature. The reason why returns to experience and job destruction rates play such an important role in wages, employment, and earnings has to do with the search friction: hiring a worker requires a firm to incur a fixed cost for the chance to start a long-term relationship. Firms are more willing to hire workers with larger surpluses, although, in equilibrium, firms make no profits, as more entry reduces the chance of a successful hire. Workers with higher returns to experience and lower separation rates produce a higher expected surplus, which induces more job posting, higher job-finding rates, a better bargaining position, and better wages during bargaining.

The natural next step in this research is to endogenize returns to experience and job separation rates. This step would require enriching the model considerably, or focusing on a more narrow set of demographic groups, as is standard in the literature.

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Appendix A: Characterization of the Model Solution

Appendix A.1: Solution for $a_R - 1$

Workers work until age $a_R - 1$. Denote by $x_{R-1} \equiv x\left(e, a_R - 1, \bar{E}, i\right)$ the final state of an employed worker, just before retirement. Using equations (3), (6), and (7), the Nash Bargaining solution (10) for the final state simplifies to

$$h\left(x_{R-1}\right) - w(x_{R-1}) = \Theta\left(x_{R-1}\right)\left[w(x_{R-1}) - \bar{c}_i^{\bar{U}}\left(e, a_R - 1\right) + \beta \Delta R_i\left(e+1, a_R\right)\right],$$

where $\Delta R_i\left(e+1, a_R\right) = R_i\left(e+1, a_R\right) - R_i\left(e, a_R\right)$ is the increase in the value of retirement due to an extra year of experience at the point of retirement. This equation provides a solution for the last period wages as

$$w(x_{R-1}) = \frac{h\left(x_{R-1}\right) + \Theta\left(x_{R-1}\right)\left[\bar{c}_i^{\bar{U}}\left(e, a_R - 1\right) - \beta \Delta R_i\left(e+1, a_R\right)\right]}{1 + \Theta\left(x_{R-1}\right)}. \tag{21}$$

According to this expression, wages are a weighted average between a worker's human capital and the level of consumption of the unemployed net of gains in the value of retirement. If the worker has all the bargaining power ($\Theta\left(x_{R-1}\right) = 0$), wages equal human capital. At the other extreme, if the firm holds all the power ($\Theta\left(x_{R-1}\right) = \infty$), wages equal consumption of the unemployed minus any gains in the value of retirement from the added experience of being employed.

The solution for the final value of the firm is then given by

$$J(x_{R-1}) = \left(1 - \phi\left(x_{R-1}\right)\right)\left[h\left(x_{R-1}\right) - \bar{c}_i^{\bar{U}}\left(e, a_R - 1\right) + \beta \Delta R_i\left(e+1, a_R\right)\right]. \tag{22}$$

The final value of the firm is a fraction of the surplus of the match, which includes production plus added value of retirement of a worker minus consumption of an unemployed worker. Assumption 1 guarantees that $J(x_{R-1})$ is positive. The final value of the firm can be used to determine the final labor market tightness rate at age $a_R - 2$. Using equation (4) and the definition of $q(x)$, a firm's probability of filling a vacancy, we have

$$\theta_i^s\left(e, a_R - 2\right) = \frac{v_i^s\left(e, a_R - 2\right)}{u_i^s\left(e, a_R - 2\right)} = \left[\frac{\beta A_i\left(e, a_R - 2, s\right)}{\kappa_i\left(e, a_R - 2, s\right)} J(x_{R-1})\right]^{1/\alpha}. \tag{23}$$

This expression, together with (22), shows that vacancies are more abundant for workers with higher human capital, lower outside consumption, and in more efficient labor markets characterized by a higher A and a lower κ. The model predicts, for example, that experienced workers and immigrants with lower outside options will have more open vacancies, all else being equal. The final job-finding rate can be solved as

$$f_i^s(e, a_R-2)^\alpha = \frac{A_i(e, a_R-2, s)}{\kappa_i\,(e, a_R-2, s)^{1-\alpha}}\,(J(x_{R-1}))^{1-\alpha}\,. \tag{24}$$

The expression (24) states that job-finding rates are higher in markets with more efficient matching, lower costs of posting vacancies, and higher values of active firms.

Appendix A.2: Proof of proposition 1

Using the definitions of surpluses given in (13), equations (3), (4), and (10) can be written as

$$\Theta\,(x)\,S_{EU}(x) = h\,(x) - w(x) + \beta(1-\pi_{EU}(x)-\pi_{EN}(x))\Theta\,(x)\,S_{EU}(x'), \tag{25}$$

$$\kappa\,(x) = \beta A\,(x)\,\theta\,(x)^{-\alpha}\,\Theta\,(x)\,S^i_{EU}(e, a+1), \tag{26}$$

where $x' = (e+1, a+1, \bar{E}, i)$. Moreover, equations (6) and (7) read

$$E(x) = w(x) + \beta\left[E(x') - \pi_{EU}(x)S_{EU}\left(x'\right) - \pi_{EN}(x)S_{EN}\left(x'\right)\right]; \tag{27}$$

$$\begin{aligned} U(x) &= c_i^{\bar{U}}\,(e,a) + \beta\left[U_i(e,a+1) + f_i^{\bar{U}}(e,a)S^i_{EU}\,(e,a+1) + \bar{\pi}_{UN}(x)S^i_{NU}\,(e,a+1)\right] \\ &= c_i^{\bar{U}}\,(e,a) + \beta\left[\begin{array}{c} U(x') - \Delta U(x') + f_i^{\bar{U}}(e,a)S_{EU}\,(e,a+1) \\ +\bar{\pi}_{UN}(x)S_{NU}\,(e,a+1) \end{array}\right]. \end{aligned}$$

Subtracting the second equation from the first one,

$$\begin{aligned} S_{EU}\,(x) &= w(x) - c_i^{\bar{U}}\,(e,a) + \\ &\quad \beta\left[\begin{array}{c} (1-\pi_{EU}(x))\,S_{EU}\,(x') + \Delta U\,(x') - f_i^{\bar{U}}(e,a)S^i_{EU}\,(e,a+1) \\ -\pi_{EN}(x)S_{EN}\,(x') - \bar{\pi}_{UN}(x)S^i_{NU}\,(e,a+1) \end{array}\right] \end{aligned}$$

or

$$S_{EU}\,(x) = w(x) - c_i^{\bar{U}}\,(e,a) + \beta E\left[\widetilde{S}^i_{EU}\,(e,a+1)\right], \tag{28}$$

where $E\left[\widetilde{S}^i_{EU}\,(e,a+1)\right]$ is the expected surplus at age $a+1$ of an employed worker in state $(e, a+1)$. It is defined as

$$E\left[\widetilde{S}^i_{EU}\,(e,a+1)\right] = \left[\begin{array}{c} (1-\pi_{EU}(x))\,S_{EU}\,(x') - \pi_{EN}(x)S_{EN}\,(x') - \bar{\pi}_{UN}(x)S^i_{NU}\,(e,a+1) \\ -f_i^{\bar{U}}(e,a)S^i_{EU}\,(e,a+1) + \Delta U\,(x') \end{array}\right].$$

Similarly, rewrite (8) as

$$\begin{aligned}N(x) &= c_i^{\bar{N}}(e,a) + \beta\left[N_i(e,a+1) + f_i^{\bar{N}}(e,a)S_{EN}^i(e,a+1) + \bar{\pi}_{NU}(x)S_{UN}^i(e,a+1)\right] \\ &= c_i^{\bar{N}}(e,a) + \beta\left[N(x') - \Delta N(x') + f_i^{\bar{N}}(e,a)S_{EN}^i(e,a+1) - \bar{\pi}_{NU}(x)S_{NU}^i(e,a+1)\right].\end{aligned}$$

Subtracting this equation from (27) leads to

$$\begin{aligned}S_{EN}(x) &= w(x) - c_i^{\bar{N}}(e,a) + \\ &\quad \beta\left[\begin{array}{c} S_{EN}(x') + \Delta N(x') - f_i^{\bar{N}}(e,a)S_{EN}^i(e,a+1) \\ -\pi_{EU}(x)S_{EU}(x') - \pi_{EN}(x)S_{EN}(x') + \bar{\pi}_{NU}(x)S_{NU}^i(e,a+1)\end{array}\right]\end{aligned}$$

or

$$S_{EN}(x) = w(x) - c_i^{\bar{N}}(e,a) + \beta E\left[\widetilde{S}_{EN}^i(e,a+1)\right], \tag{29}$$

where

$$E\left[\widetilde{S}_{EN}^i(e,a+1)\right] = \left[\begin{array}{c}(1-\pi_{EU}(x))\,S_{EN}(x') - f_i^{\bar{N}}(e,a)S_{EN}^i(e,a+1) \\ -\pi_{EU}(x)S_{EU}(x') + \bar{\pi}_{NU}(x)S_{NU}^i(e,a+1) + \Delta N(x')\end{array}\right]$$

is the expected value of the future surplus, at $a+1$, of an employed worker at state $(e, a+1)$.

Equations (3), (25), (26), (28), and (29) form a system of five equations in four unknowns that can be solved for each (i, e, a) state given future values of those same variables: $\{J(x), S_{EU}(x), \theta^s(x), w(x), S_{EN}(x)\}_{(i,e,a)}$. Equation (26) can be used to directly solve for $\theta(x)$ as a function of $J_i(e, a+1)$. To solve for $w(x)$, use (25) and (28) to obtain

$$\begin{aligned}&\Theta(x)\left[w(x) - c_i^{\bar{U}}(e,a) + \beta E\left[\widetilde{S}_{EU}^i(e,a+1)\right]\right] \\ =\ & h(x) - w(x) + \beta\left[(1-\pi_{EU}(x) - \pi_{EN}(x))\Theta(x)\,S_{EU}(x')\right].\end{aligned}$$

Solving for $w(x)$ gives

$$w(x) = \frac{h(x) + \Theta(x)\,c_i^{\bar{U}}(e,a) + \beta\Theta(x)\,\Omega(x)}{1+\Theta(x)},$$

where $\Omega(x) = (1-\pi_{EU}(x) - \pi_{EN}(x))S_{EU}(x') - E\left[\widetilde{S}_{EU}^i(e,a+1)\right]$. Notice that

$$\begin{aligned}\Omega(x) &= (1-\pi_{EU}(x) - \pi_{EN}(x))S_{EU}(x') - E\left[\widetilde{S}_{EU}^i(e,a+1)\right] \\ &= (1-\pi_{EU}(x) - \pi_{EN}(x))S_{EU}(x') - (1-\pi_{EU}(x))\,S_{EU}\left(x'\right) + \pi_{EN}(x)S_{EN}\left(x'\right) \\ &\quad +\bar{\pi}_{UN}(x)S_{NU}^i(e,a+1) + f_i^{\bar{U}}(e,a)S_{EU}^i(e,a+1) - \Delta U\left(x'\right) \text{ or}\end{aligned}$$

$$\begin{aligned}\Omega(x) &= \pi_{EN}(x)\left[S_{EN}\left(x'\right) - S_{EU}(x')\right] + \bar{\pi}_{UN}(x)S_{NU}^i(e,a+1) \\ &\quad +f_i^{\bar{U}}(e,a)S_{EU}^i(e,a+1) - \Delta U\left(x'\right).\end{aligned}$$

Appendix A.3: Solution for $a < a_R - 1$

To gain some further intuition about the determination of wages, consider the determination of wages two periods before retirement. Denote by $x_{R-2} = x(e, a_R - 2, \bar{E}, i)$. First, using the solutions already obtained for $a = a_R - 1$, the following results can be found:

$$\begin{aligned}
S_{EU}\left(x_{R-1}\right) &= w(x_{R-1}) - \bar{c}_i^{\bar{U}}\left(e, a_R - 1\right) + \beta \Delta R_i \left(e+1, a_R\right), \\
S_{EN}\left(x_{R-1}\right) &= w(x_{R-1}) - \bar{c}_i^{\bar{N}}\left(e, a_R - 1\right) + \beta \Delta R_i \left(e+1, a_R\right), \\
S_{NU}\left(x_{R-1}\right) &= \bar{c}_i^{\bar{N}}\left(e, a_R - 1\right) - c_i^{\bar{U}}\left(e, a_R - 1\right), \\
\Delta U^i \left(e+1, a_R - 1\right) &= \bar{c}_i^{\bar{U}}(e+1, a_R - 1) - \bar{c}_i^{\bar{U}}(e, a_R - 1) + \beta \Delta R_i \left(e+1, a_R\right).
\end{aligned}$$

Furthermore, suppose just for illustration that $\bar{c}\left(x\right) = \bar{c}$ for all x. In that case, we can show that surpluses can be written as

$$\begin{aligned}
S_{EU}\left(x_{R-1}\right) &= w(x_{R-1}) - \bar{c},\ S_{EN}\left(x_{R-1}\right) = w(x_{R-1}) - \bar{c}, \\
S_{NU}\left(x_{R-1}\right) &= 0,\ \Delta U^i \left(e+1, a_R - 1\right) = 0, \text{ and} \\
W\left(x_{R-2}\right) &= f_i^{\bar{U}}(e, a_R - 2) S_{EU}^i\left(e, a_R - 1\right).
\end{aligned}$$

Plugging these results into (14), it follows that

$$w(x_{R-2}) = \frac{h\left(x_{R-2}\right) + \Theta\left(x_{R-2}\right)\left[\bar{c} + \beta f_i^{\bar{U}}(e, a_R - 2)\left(w(x_{R-1}) - \bar{c}\right)\right]}{1 + \Theta\left(x_{R-2}\right)}.$$

Appendix B: Identification and calibration strategy

The model calibration uses average wages and average job-finding rates at each age to calibrate human capital and matching efficiency parameters for any given age and demographic group. The calibration of the key parameters $A_i\left(a\right)$, $\psi_i(a)$, $r_i\left(a\right)$, and y_i come from an iteration process that starts with an initial guess of $m_i^s(e, a)$ and y_i which are recursively revised until convergence. Define average wages, average human capital, average outside consumption, and average job-finding rates at age a as

$$w_i(a) = \frac{\sum_e m_i^{\bar{E}}\left(e, a\right) w_i(e, a)}{\sum_e m_i^{\bar{E}}\left(e, a_R\right)}, \tag{30}$$

$$h_i(a) = \frac{\sum_e m_i^{\bar{E}}\left(e, a\right) h_i(e, a)}{\sum_e m_i^{\bar{E}}\left(e, a_R\right)}, \tag{31}$$

$$c_i(a) = \frac{\sum_e m_i^{E}\left(e, a\right) \bar{c}_i^{U}(e, a)}{\sum_e m_i^{E}\left(e, a_R\right)}, \tag{32}$$

$$f_i^{\bar{U}}\left(a\right) = \frac{\sum_e m_i^{\bar{U}}\left(e, a\right) f_i^{\bar{U}}\left(e, a\right)}{\sum_e m_i^{\bar{U}}\left(e, a\right)}, \text{ and} \tag{33}$$

$$f_i^{\bar{N}}(a) = \frac{\sum_e m_i^{\bar{N}}(e,a)\, f_i^{\bar{U}}(e,a)}{\sum_e m_i^{\bar{N}}(e,a)}. \tag{34}$$

Appendix B.1: Calibration for $a = a_R - 1$

We are now ready to describe the benchmark calibration of human capital parameters and matching efficiencies. The reverse engineering starts backwards from $a_R - 1$. According to (21), (30), (31), and (32), the average wage at age $a_R - 1$ satisfies

$$\begin{aligned} w_i(a_R - 1) &= \frac{\sum_e m_i^{\bar{E}}(e, a_R - 1)\, w_i(e, a_R - 1)}{\sum_e m_i^{\bar{E}}(e, a_R - 1)} \\ &= \frac{\sum_e m_i^{\bar{E}}(e, a_R - 1) \frac{\left[h_i(e,a_R-1)+\Theta_i(a)\left(c_i^{\bar{U}}(e,a_R-1)-\beta\Delta R_i(e+1,a_R)\right)\right]}{1+\Theta_i(a)}}{\sum_e m_i^{\bar{E}}(e, a_R - 1)} \\ &= \frac{h_i(a_R - 1) + \Theta_i(a)\left[c_i(a_R - 1) - \beta \Delta R_i(a_R)\right]}{1 + \Theta_i(a)}, \end{aligned}$$

where

$$\Delta R_i(a_R) = \frac{\sum_e m_i^{\bar{E}}(e,a)\, \Delta R_i(e+1, a_R)}{\sum_e m_i^{\bar{E}}(e, a_R)}. \tag{35}$$

Given data for $w_i(a_R - 1)$, this expression could be used to solve for $h_i(a_R - 1)$ as

$$h_i(a_R - 1) = w_i(a_R - 1)\left(1 + \Theta_i(a)\right) - \Theta_i(a)\left(c_i^{\bar{U}}(a_R - 1) - \beta \Delta R_i(a_R)\right). \tag{36}$$

The calculated $h_i(a_R - 1)$ should be equal to the analytical average human capital obtained from the assumed functional form $h_i(e,a)$ $=y_i exp(r_i(a)e)$ across experiences at age $a = a_{R-1}$. This provides the following equation used to solve for $r_i(a_R - 1)$:

$$h_i(a_R - 1) = y_i \frac{\sum_e m_i^E(e, a_R - 1)\, exp(r_i(a_R - 1)e)}{\sum_e m_i^E(e, a_R - 1)}. \tag{37}$$

The calibrated value of $r_i(a_R - 1)$ is then used to calculate human capitals $h_i(e, a_R - 1)$ and wages, not just average wages, according to (21) as

$$w_i(e, a_R - 1) = \frac{1}{1 + \Theta_i(a)}\left[h_i(e, a_R - 1) + \Theta_i(a)\left(c_i^{\bar{U}}(e, a_R - 1) - \beta \Delta R_i(e + 1 a_R)\right)\right].$$

These wages can then be plugged into (3), (6), (7), and (8) to find $J_i(e, a_R - 1)$, $E_i(e, a_R - 1)$, $U_i(e, a_R - 1)$, and $N_i(e, a_R - 1)$ as well as the surpluses defined by (13) for $a = a_R - 1$.

Appendix B.2: Calibration for $a < a_R - 1$.

Given the values of $J_i(e, a+1)$, average job-finding rates for age a can be found using (18), (33), and (34). In particular,

$$f_i^{\bar{U}}(a) = A_i(a)^{\frac{1}{\alpha}} \frac{\sum_e m_i^{\bar{U}}(e,a)\left(\beta J_i(e, a+1)/\kappa_i(e,a)\right)^{\frac{1-\alpha}{\alpha}}}{\sum_e m_i^{\bar{U}}(e,a)}$$

or solving for $A_i(a)$:

$$A_i\left(a,\bar{U}\right)=A_i(a)=\left[\frac{f_i^{\bar{U}}\left(a\right)\sum_e m_i^{\bar{U}}\left(e,a\right)}{\sum_e m_i^{\bar{U}}\left(e,a\right)\left(\beta J_i(e,a+1)/\kappa_i\left(e,a\right)\right)^{\frac{1-\alpha}{\alpha}}}\right]^{\alpha}.$$

Similarly,

$$A_i\left(a,\bar{N}\right)=\psi_i(a)A_i(a)=\left[\frac{f_i^{\bar{N}}\left(a\right)\sum_e m_i^{\bar{N}}\left(e,a\right)}{\sum_e m_i^{\bar{N}}\left(e,a\right)\left(\beta J_i(e,a+1)/\kappa_i\left(e,a\right)\right)^{\frac{1-\alpha}{\alpha}}}\right]^{\alpha}.$$

These two expressions provide the calibrated values of $A_i\left(a\right)$ and $\psi_i(a)$ given the data on average values of job-finding rates for the unemployed and nonparticipants. These formulas are valid for all ages. Given these parametric values, job-finding rates for all e, not just on average, $f_i^{\bar{U}}\left(e,a\right)$ and $f_i^{\bar{N}}\left(e,a\right)$, can then be calculated using (16). One can the use these job-finding rates as well as the surpluses already obtained for $a+1$ to calculate $\Omega(x)$ as defined by (17). Next, define the expression of $\Omega_i^{\bar{E}}\left(a\right)$ as

$$\Omega_i^{\bar{E}}\left(a\right)=\frac{\sum_e m_i^{\bar{E}}\left(e,a\right)\Omega_i^{\bar{E}}\left(e,a\right)}{\sum_e m_i^{\bar{E}}\left(e,a\right)}.$$

According to (14), average wages satisfy

$$\begin{aligned} w_i(a) &= \frac{1}{1+\Theta_i\left(a\right)}\sum_e\frac{m_i^{\bar{E}}\left(e,a\right)}{\sum_e m_i^{\bar{E}}\left(e,a\right)}\left[\begin{array}{c} h_i\left(e,a\right)+ \\ \Theta_i\left(a\right)\left(c_i^{\bar{U}}+\beta\Omega_i^{\bar{E}}\left(e,a\right)\right)\end{array}\right] \\ &= \frac{1}{1+\Theta_i\left(a\right)}\left[h_i\left(a\right)+\Theta_i\left(a\right)\left(c_i^{\bar{U}}+\beta\Omega_i^{\bar{E}}\left(a\right)\right)\right].\end{aligned}$$

Given data for $w_i(a)$, this expression could be used to solve for $h_i(a)$ as

$$h_i\left(a\right)=w_i(a)\left(1+\Theta_i\left(a\right)\right)-\Theta_i\left(a\right)\left(c_i^{\bar{U}}+\beta\Omega_i^{\bar{E}}\left(a\right)\right). \tag{38}$$

The calculated sequence of $h_i\left(a\right)$ should again be equal to the analytical average human capital obtained from the assumed functional form $h_i(e,a)$ $=y_i exp(r_i(a)e)$. This provides the following set of equations that are used to solve for y_i and $r_i(a)$:

$$h_i(0)=y_i, h_i(a)=y_i\frac{\sum_e m_i^{\bar{E}}\left(e,a\right)exp(r_i(a)e)}{\sum_e m_i^{\bar{E}}\left(e,a\right)}. \tag{39}$$

Given y_i and $r_i(a)$, then $h_i(e,a)$ $=y_i exp(r_i(a)e)$ can be obtained for all e as well as wages, not just average wages, according to (14). Wages can then be plugged into (3), (6), (7), and (8) to find $J_i(e,a)$, $E_i(e,a)$, $U_i(e,a)$, and $N_i(e,a)$ as well as the surpluses defined by (13) for a.

The process just described delivers full sequences of value functions, human capital, wages, and job-finding rates for all (e,a,i,s). The job-finding rates can then be used along with other exogenous flows to update the guessed sequence of $m_i^s(e,a)$ using (11) and (12).

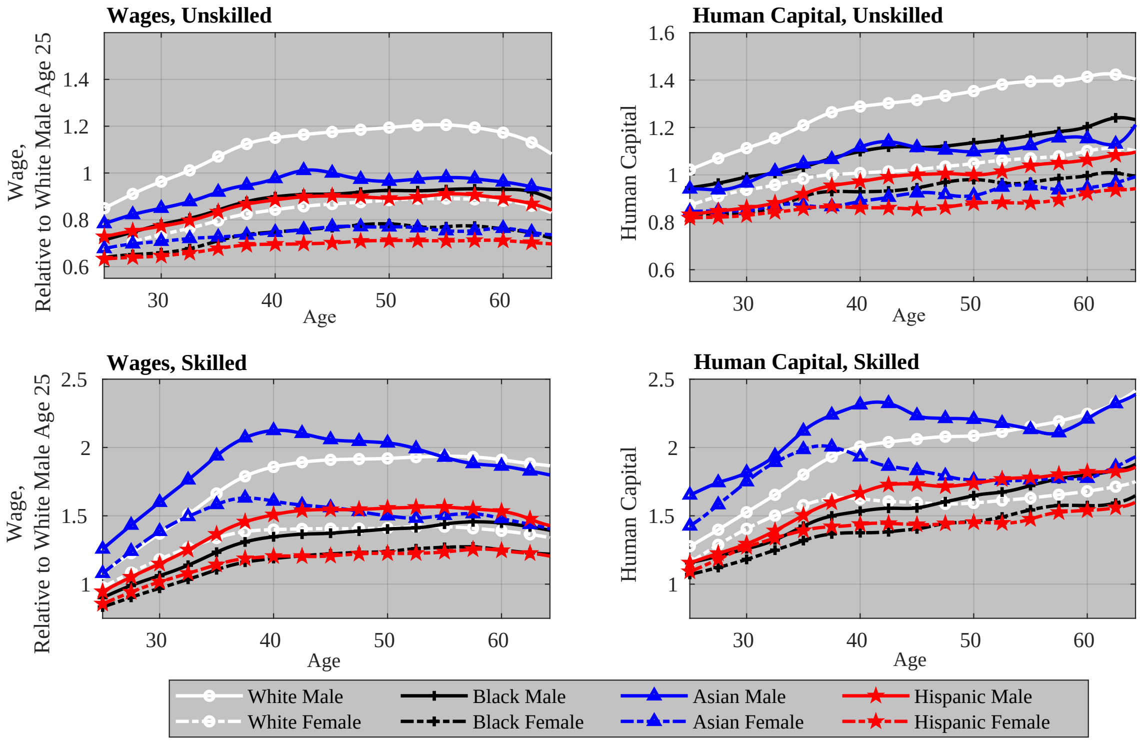


Figure C3.1: Wage and human capital profiles over the life cycle for skilled and unskilled workers, relative to the wage of an average 25-year-old White male.

Appendix C: Detailed calibration results

Appendix C.1: Reverse-engineered human capital profiles for skilled and unskilled workers

We next describe the differences in human capital profiles between different skill groups. Figure C3.1 shows, not surprisingly, that unskilled groups have lower starting levels and growth rates of human capital compared to the skilled. Also, human capital levels vary less between gender and race for unskilled compared to skilled. Within race, males have higher levels of human capital over the life cycle for both skilled and unskilled compared to females. Males also have steeper growth profiles of human capital: while for most male groups human capital is strictly increasing over time, White and Hispanic females face a stagnating human capital growth between ages 35 and 50. The human capital of skilled Black females follows a similar growth profile to males—it keeps increasing over the whole life cycle. Stagnating human capital growth for certain female groups is likely related to career breaks: as many women leave the labor market during prime working ages due to family reasons, average returns to experience for those groups are lower.

Within gender and skill, we also find fairly large differences in human capital profiles for different races, and these differences increase over the life cycle. For the unskilled, White males and females have higher human capital levels over the whole life cycle compared to other races. For the skilled, Asian males have the highest human capital until age 55, when White males take the lead. Black and Hispanic males have significantly lower

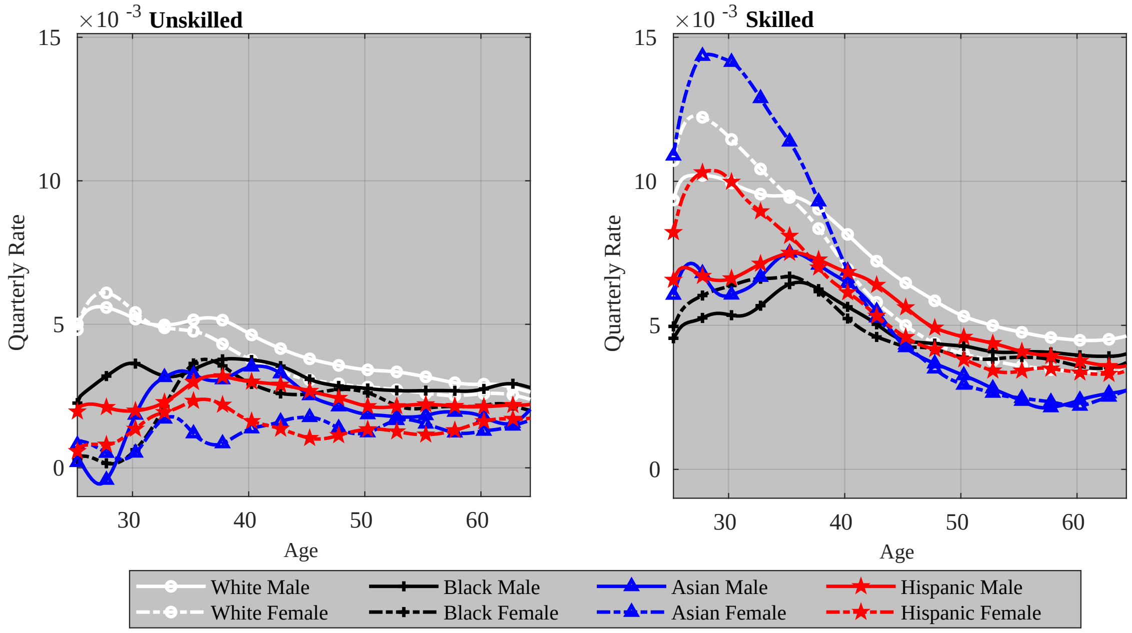


Figure C3.2: Returns to experience for skilled and unskilled workers.

human capital levels compared to Asian and White males, Hispanics having somewhat higher human capital compared to Black males. Skilled Asian females have the highest human capital over the life cycle compared to other females groups, followed by White females. Again, Black and Hispanic females have similar human capital levels over the life cycle, but significantly lower compared to Asian and White females. The racial gaps in human capital are, however, smaller for women than for men.

Figure C3.2 shows specifically the reverse-engineered returns to experience ($r_i(a)$) for both skilled and unskilled workers. Returns to experience gaps determine the gaps in the human capital growth rates. Skilled workers have higher $r_i(a)$ than unskilled workers, as can be seen in the human capital profiles. Returns to experience seem to decrease for older workers, and this pattern is especially prominent for the skilled groups. Returns to experience within the unskilled are the highest for White males and females followed by other male groups and Black females. In general, males have higher returns to experience than females within a race.

Figure C3.3 shows wage-to-human capital profiles for different demographic groups, which represent the gross profits of firms hiring a member of a given demographic group. Gross profits are higher for demographic groups who have a lower long-time value of the match. The intuition is that firms will attempt to recover their vacancy posting costs, and if the long-term value of the match is low, firms are requiring a higher share of the worker's human capital at the current period to cover the cost. Gross profits have a U-shape for many groups: required profits are higher for younger workers, decreased for the prime-age workers, and then start increasing again towards retirement. There is also gender and racial variation in the gross profits for both unskilled and skilled workers. Firms require lower gross profits from males within a race, as their long-term value for a firm is expected

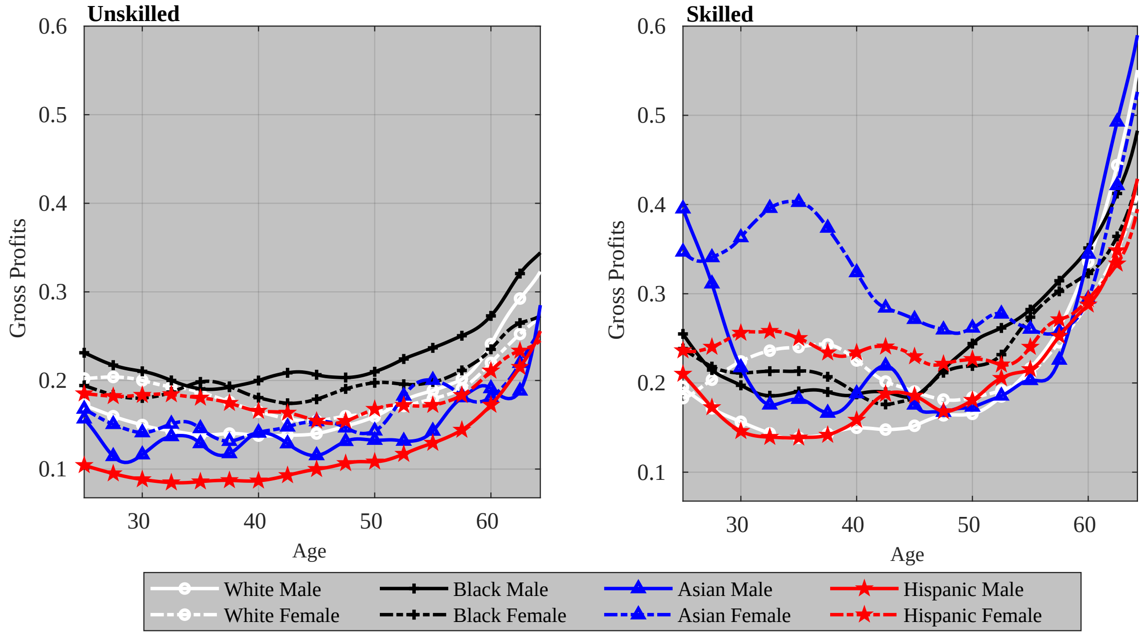


Figure C3.3: Gross profits per worker, skilled and unskilled.

to be higher. The only exception is Blacks, for whom the gross profits of males are similar or even higher than the gross profits of females. Within unskilled workers, Asian and especially Hispanic males have the lowest gross profits, followed by Whites, while the gross profits for Black males are the highest. For females under age 45, Asians have the lowest gross profits, while other female groups have fairly similar levels, but after age 45 the gross profits for every female group converge. The patterns for skilled females are very different: Asian females have notably high gross profits. This pattern is likely arising from the fact that Asian females have very high human capital and, as the hiring costs are assumed to be increasing in a worker's human capital, the costs of hiring these workers are high. That, combined with a relatively low long-term value of the match, leads to very high gross profits. Hispanic females have the second-highest gross profits followed by Whites, and skilled Black females have the lowest gross profits. Among males, Black males again have the highest gross profits. The gross profits of White and Hispanic males are at similar levels over the life cycle. For Asian males, they first have as high or even higher gross profits than Black males, but after age 45 they converge to the ones of Hispanic and White males.

Appendix C.2: Reverse-engineered matching efficiencies for skilled and unskilled workers

Overall, matching efficiencies are higher for unskilled groups than skilled groups (Figure C3.4). Unskilled groups have more variation in the matching efficiencies compared to skilled groups. Also, the As of unskilled males are decreasing relatively more with age compared to women and skilled men, which could reflect the fact that unskilled males are more likely to be working in occupations requiring physical labor and that aging is

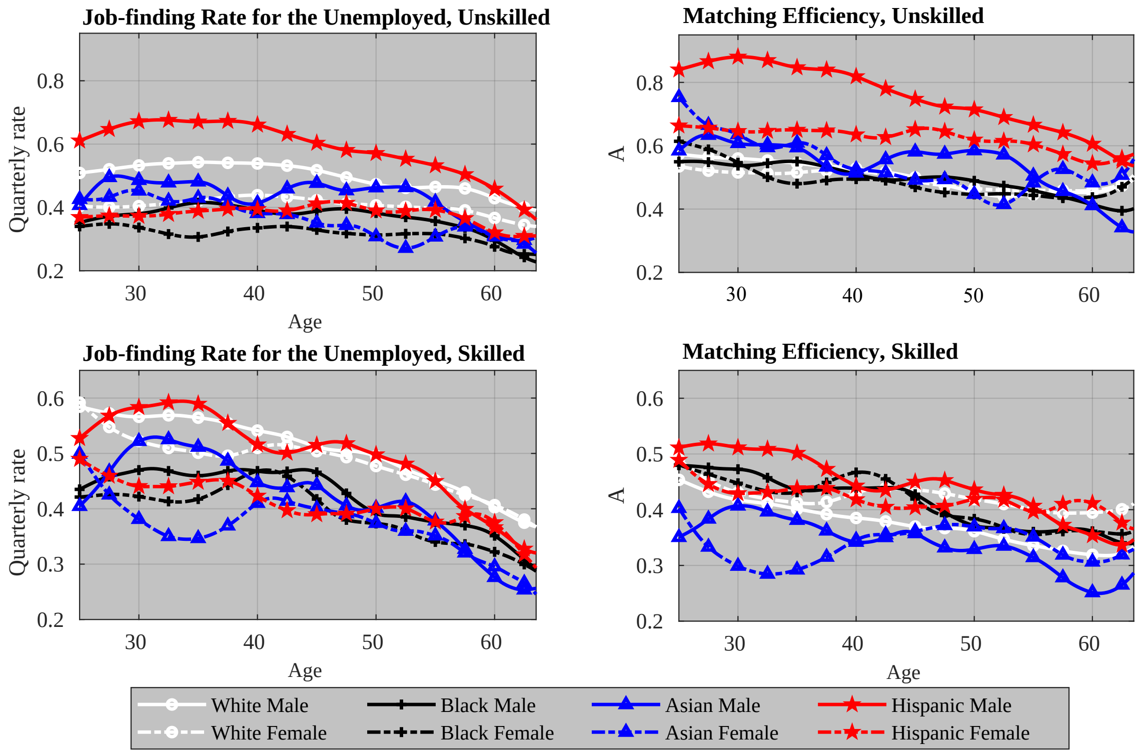


Figure C3.4: Job-finding rates for unemployed and matching efficiencies over the life cycle for skilled and unskilled workers.

reducing productivity more in these occupations.

Similarly, as with human capital, males tend to have higher matching efficiencies within race and skill compared to females. This is especially pronounced for unskilled and younger workers. It is likely that younger female workers with lower skills may be presumed less attached to the labor force, which then affects their job-finding rates. Within skilled groups, the gender gap in matching efficiency for Blacks and Whites is quite small, and White females have a higher matching efficiency compared to White males after age 40. Young skilled Asians have the widest gender gap compared to other skilled groups, Asian women between ages 25 and 40 having significantly weaker matching efficiency. This gap, however, closes towards the end of the life cycle. Skilled Hispanics also have a wider gender gap compared to Blacks and Whites, but more modest than unskilled Hispanics.

When it comes to racial differences in matching efficiencies, Hispanics tend to do better in almost all gender-skill groups: Hispanic males have the highest matching efficiencies among both skilled and unskilled males, while the same is true for unskilled Hispanic females. Within unskilled females and males, Hispanics are followed by Asians and Whites, Blacks coming last. When it comes to skilled males, the other three races have fairly similar matching efficiencies over the life cycle. Among skilled females, White females have the highest matching efficiencies over the whole life cycle, followed by Hispanics and Blacks. As mentioned before, skilled Asian females have the lowest matching efficiency early in life but it starts to catch up with the ones of Hispanics and Blacks after age 40.

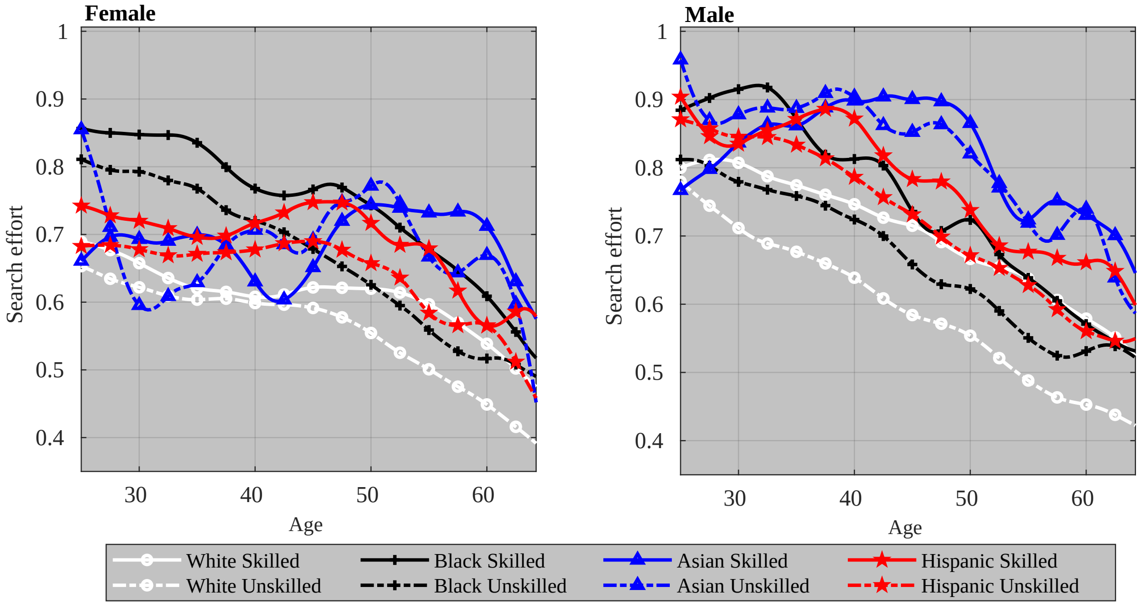
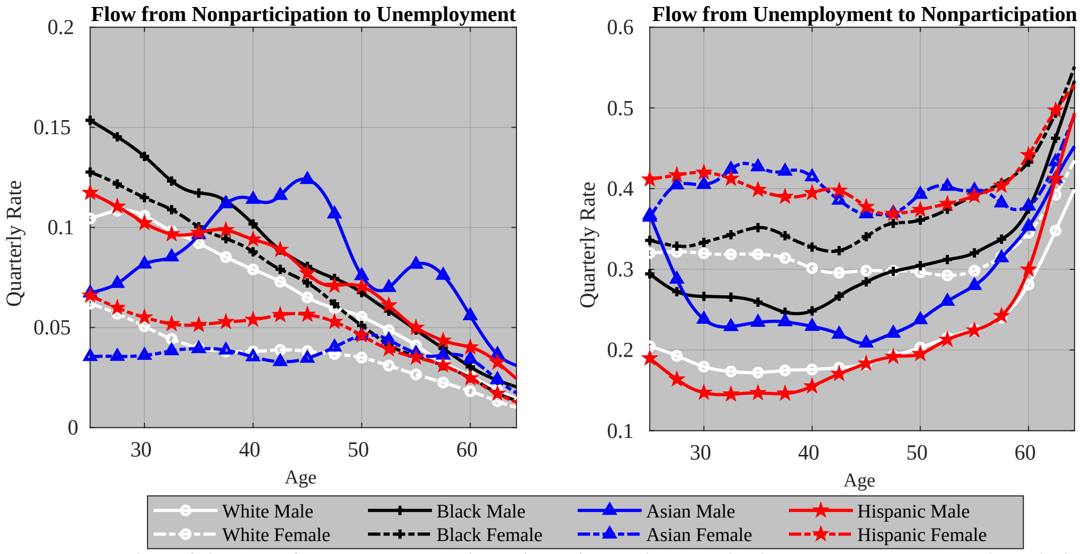


Figure C3.5: Search effort, $\psi_i(a)$ of nonparticipants, skilled and unskilled.

Figure C3.5 presents the reverse-engineered search effort of nonparticipants for different groups. The identification assumption in the calibration was that, we assume that the matching efficiencies, A, are the same for the unemployed and the nonparticipants, and that the search effort of the unemployed is always 1. Thus, $\psi_i(a)$ captures the differences in job-finding rates between unemployed and nonparticipants for otherwise similar workers. The interpretation is that nonparticipants are typically less attached to the labor force for various reasons, which is reflected in the lower job-finding rates of nonparticipants and is captured by the lower search effort.

The most obvious trend in search efforts over the life cycle is that the search effort is the highest for young workers and starts decreasing for the majority of the groups with age. This is not a surprising result since older workers are likely to be less attached to the labor force for various reasons: older workers are more likely to have issues related to health affecting their willingness to search for work, and they may also be more discouraged to look for work because the probability of finding a job decreases with age.

The skilled have higher search effort compared to the unskilled for all the other races except for Asians. For Asians, the search effort for the skilled and the unskilled are quite similar, but the ranking varies over life. There is also a gender gap in the search effort for all the other groups except unskilled Blacks, but the gender gap decreases or closes after age 40. The lower search effort of females is thus most likely related to child-rearing responsibilities. The search efforts of unskilled Black males and females are almost equal, which either reflects that the search effort of Black females is atypically high, the search effort of Black males is atypically low, or a combination of both, compared to other gender groups. This result likely reflects the fact that Blacks are less likely to be married (see, for example, Caucutt, Guner, and Rauh (2018) and Bloom and Ang (2020)) and Black women are more likely to be single-mothers compared to other races, which then shows up as a



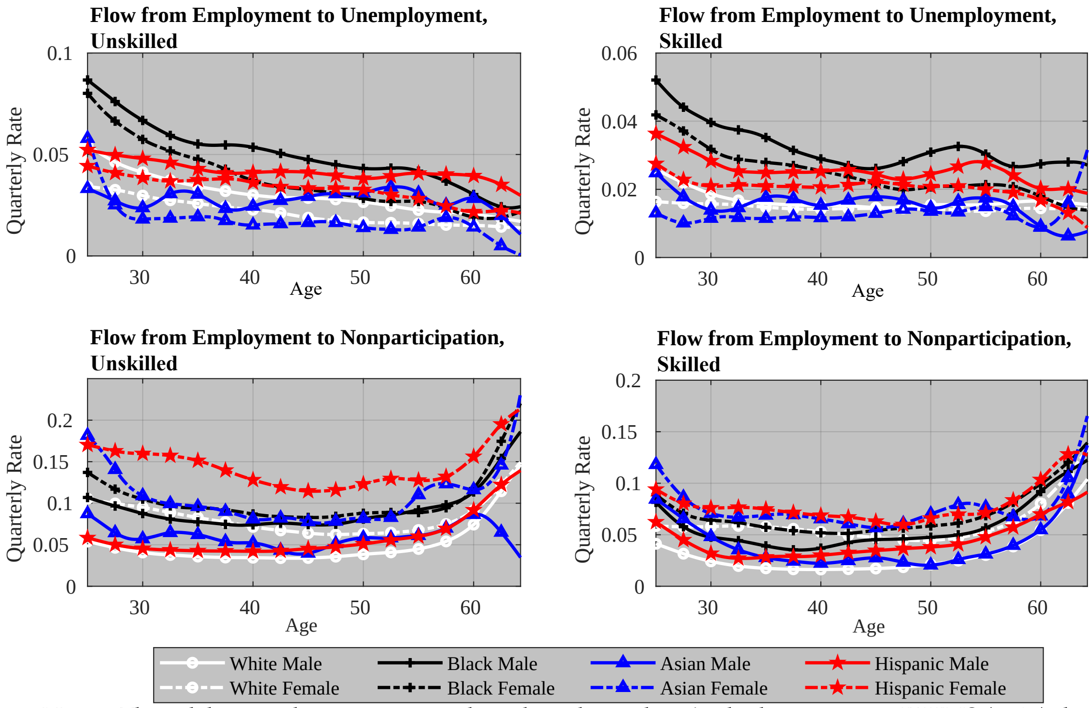
Notes: These labor market statistics are based on the authors' calculations using IPUMS (2018) data for years 1998–2018.

Figure C3.6: Average transition flows between nonparticipation and unemployment.

higher attachment to the labor force and a higher search effort of Black females. While Blacks have the lowest gender gap also among the skilled, the highest gender gaps are among Asians and Hispanics.

Racial differences in search effort vary between gender. While Asian males have the highest search effort within each skill level, followed by Hispanics and Blacks, Black females have the highest search effort among females. Only among unskilled females do Asians and Hispanics have a higher search effort after age 40 than Blacks. Whites always have the lowest search effort within a gender-skill group.

Figures C3.6 and C3.7 present the average transition flows between unemployment and nonparticipation, and the job destruction rates for the skilled and unskilled workers, π^i_{EU} and π^i_{EN}. Figure C3.6 shows that females are more likely to move from unemployment to nonparticipation, and less likely to move back to unemployment compared to males. Figure C3.7 shows significant variation in the job destruction rates within and between skill groups.



Notes: These labor market statistics are based on the authors' calculations using IPUMS (2018) data for years 1998–2018.

Figure C3.7: Job destruction rates to unemployment and nonparticipation for skilled and unskilled workers.

Appendix D: Detailed decomposition results

This section presents the detailed decomposition results for the overall, skill, gender, and race gaps, including various labor market gaps. Table D3.1 shows the decomposition of the overall gaps in the labor market outcomes, Table D3.2 the decomposition of the gender gaps, Table D3.3 the decomposition of the skill gaps, and Table D3.4 the decomposition of the race gaps. The outcomes for which the gaps and decomposition are calculated are average hourly wages (Wage), employment rate (Empl), unemployment rate (Unemp), labor force participation (Part) and nonparticipation (Non-part) rates, labor market tightness rates for the unemployed (θ^U) and nonparticipants (θ^N), job-finding rates for the unemployed (π_{UE}) and nonparticipants (π_{NE}), and lifetime earnings (W). The tables display the contributions of each individual variables in generating the calculated gaps as well as the absolute contributions of each individual variable. Absolute contributions are calculated by dividing an individual variable's contribution by the sum of *absolute* values of individual contributions.

Table D3.1: Detailed decomposition of the overall gaps

	Wage	Empl	Unemp	Part	Non-part	θ^U	θ^N	π_{UE}	π_{NE}	W
Average gap (weighted)	10.27	13.5%	-0.9%	12.6%	-12.6%	19.9%	7.8%	4.2%	1.9%	37.49
Explained gap	7.96	14.7%	-0.1%	14.5%	-14.5%	19.1%	7.9%	4.3%	2.5%	27.97
Initial human capital (*y*)	3.78	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	10.08
Matching efficiency (*A*)	-0.05	-0.5%	0.2%	-0.4%	0.4%	-0.7%	-0.1%	-1.7%	-0.4%	-0.25
Search effort, nonparticipants (ψ)	0.18	2.0%	0.0%	2.0%	-2.0%	-2.3%	2.5%	-0.7%	1.9%	1.14
Returns to experience (r)	2.17	1.2%	-0.2%	1.0%	-1.0%	9.5%	3.0%	3.1%	0.9%	8.45
Separation rate to unempl. (π_{EU})	0.22	1.3%	-0.7%	0.6%	-0.6%	1.9%	0.5%	0.5%	0.2%	0.83
Separation rate to non-p. (π_{EN})	1.51	10.3%	-0.5%	9.8%	-9.8%	14.7%	3.7%	4.4%	0.5%	7.32
Flow unempl. to non-p. (π_{UN})	0.11	-0.2%	0.7%	0.5%	-0.5%	-3.8%	-1.4%	-1.3%	-0.5%	0.11
Flow non-p. to unempl. (π_{NU})	0.04	0.4%	0.4%	0.8%	-0.8%	-0.2%	-0.2%	-0.1%	-0.1%	0.25
Initial distribution of pop. (m_0)	0.01	0.2%	0.0%	0.1%	-0.1%	0.0%	0.0%	0.0%	0.0%	0.05
μ	1.22	2.3%	-0.3%	2.0%	-2.0%	18.0%	6.1%	5.5%	1.8%	6.84
				Absolute contributions						
	Wage	**Empl**	**Unemp**	**Part**	**Non-part**	θ^U	θ^N	π_{UE}	π_{NE}	**W**
				Human capital						
Initial human capital (*y*)	46.9%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	35.4%
Returns to experience (*r*)	26.9%	7.4%	7.3%	6.4%	6.4%	28.8%	25.8%	26.2%	20.0%	29.7%
				Matching efficiency						
Matching efficiency (*A*)	-0.7%	-3.2%	-6.0%	-2.3%	-2.3%	-2.2%	-1.1%	-14.6%	-9.1%	-0.9%
Search effort, nonparticipants (ψ)	2.2%	12.6%	-0.5%	13.2%	13.2%	-6.9%	21.9%	-6.0%	42.7%	4.0%
				Separation rates (d)						
To unemployment (π_{EU})	2.8%	8.2%	27.0%	3.9%	3.9%	5.6%	4.7%	4.4%	3.4%	2.9%
To nonparticipation (π_{EN})	18.7%	64.0%	18.3%	64.5%	64.5%	44.4%	32.1%	37.7%	11.5%	25.7%
				Others						
π_{UN}	1.3%	-1.0%	-25.3%	3.3%	3.3%	-11.5%	-12.1%	-10.7%	-10.9%	0.4%
π_{UN}	0.5%	2.6%	-15.4%	5.4%	5.4%	-0.6%	-1.7%	-0.4%	-1.7%	0.9%
m_0	0.1%	1.1%	0.2%	1.0%	1.0%	0.0%	-0.4%	0.0%	-0.7%	0.2%
Sum absolute contributions	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
				Statistical discrimination						
Total contribution	15.1%	14.6%	12.5%	13.4%	13.4%	54.4%	53.4%	46.7%	40.6%	24.0%
As share of d	70.5%	20.2%	27.7%	19.7%	19.7%	108.6%	145.1%	111.0%	272.3%	83.9%

Notes: This table displays the contributions of each variable in generating the overall gap in labor market outcomes. The overall gap in each outcome is calculated as a difference between the average outcome of skilled White males and the population-weighted average of outcome of all other groups. For example, the average gap in hourly wage rate (Wage) between the skilled White males and other groups is observed to be \$10.34 in the data. The summed up contribution of the individual model variables equals \$8.01 (Explained gap), while the remaining part of the wage gap arises from the correlations between individual variables.

Table D3.2: Detailed decomposition of the gender gaps

	Wage	Empl	Unemp	Part	Non-part	θ^{U}	θ^{N}	π_{UE}	π_{NE}	W
Average gap (weighted)	3.01	6.8%	0.4%	7.3%	-7.3%	5.1%	2.8%	3.3%	1.7%	11.51
Explained gap	2.83	8.0%	0.7%	8.7%	-8.7%	5.8%	3.4%	3.3%	2.1%	10.57
Initial human capital (y)	1.16	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	3.12
Matching efficiency (A)	0.14	1.0%	-0.1%	0.9%	-0.9%	1.0%	0.3%	2.0%	0.6%	0.48
Search effort, nonparticipants (ψ)	0.16	1.4%	0.0%	1.4%	-1.4%	-1.8%	1.9%	-0.5%	1.5%	0.87
Returns to experience (r)	0.46	0.3%	0.0%	0.2%	-0.2%	2.0%	0.6%	0.6%	0.2%	2.06
Separation rate to unempl. (π_{EU})	-0.10	-0.6%	0.2%	-0.3%	0.3%	-0.7%	-0.3%	-0.3%	-0.1%	-0.37
Separation rate to non-p. (π_{EN})	0.89	5.6%	-0.2%	5.3%	-5.3%	8.2%	2.0%	2.4%	0.4%	4.10
Flow unempl. to non-p. (π_{UN})	0.07	-0.1%	0.4%	0.2%	-0.2%	-2.6%	-0.9%	-0.8%	-0.3%	0.05
Flow non-p. to unempl. (π_{NU})	0.04	0.4%	0.5%	0.9%	-0.9%	-0.3%	-0.2%	-0.1%	-0.1%	0.23
Initial distribution of pop. (m_0)	0.01	0.1%	0.0%	0.1%	-0.1%	0.0%	0.0%	0.0%	0.0%	0.03
μ	0.48	1.0%	-0.1%	0.9%	-0.9%	7.3%	2.4%	2.2%	0.7%	2.86

Absolute contributions

	Wage	Empl	Unemp	Part	Non-part	θ^{U}	θ^{N}	π_{UE}	π_{NE}	W
Human capital										
Initial human capital (y)	38.4%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	27.6%
Returns to experience (r)	15.4%	2.7%	-2.0%	2.3%	2.3%	12.0%	9.9%	8.9%	6.1%	18.2%
Matching efficiency										
Matching efficiency (A)	4.7%	10.8%	-7.9%	9.5%	9.5%	6.2%	4.3%	29.6%	20.0%	4.2%
Search effort, nonparticipants (ψ)	5.2%	14.5%	-0.5%	14.6%	14.6%	-10.5%	30.3%	-8.0%	47.0%	7.7%
Separation rates (d)										
To unemployment (π_{EU})	-3.3%	-6.2%	16.3%	-3.7%	-3.7%	-4.4%	-4.5%	-3.9%	-2.5%	-3.3%
To nonparticipation (π_{EN})	29.4%	59.0%	-15.0%	56.9%	56.9%	49.3%	32.4%	36.1%	11.3%	36.2%
Others										
π_{UN}	2.3%	-1.5%	24.8%	2.5%	2.5%	-15.7%	-14.3%	-12.3%	-9.7%	0.4%
π_{UN}	1.2%	4.1%	33.6%	9.3%	9.3%	-1.9%	-3.8%	-1.2%	-3.4%	2.0%
m_0	0.2%	1.2%	0.0%	1.2%	1.2%	0.0%	-0.6%	0.0%	0.0%	0.3%
Sum absolute contributions	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
Statistical discrimination										
Total contribution	16.0%	10.2%	-7.6%	9.4%	9.4%	43.9%	38.3%	32.6%	22.6%	25.3%
As share of d	61.4%	19.3%	-586.7%	17.6%	17.6%	97.9%	137.4%	101.6%	255.2%	76.8%

Notes: This table displays the contributions of each variable in generating the gender gap in labor market outcomes. The gender gap in each outcome is calculated as a difference between the population-weighted average outcome of all males and the population-weighted average outcome of all females. For example, the average gap in hourly wage rate (Wage) between males and females is observed to be \$3.03 in the data. The summed up contribution of the individual model variables equals \$2.84 (Explained gap), while the remaining part of the wage gap arises from the correlations between individual variables.

Table D3.3: Detailed decomposition of the skill gaps

	Wage	Empl	Unemp	Part	Non-part	θ^U	θ^N	π_{UE}	π_{NE}	W
Average gap (weighted)	4.73	5.5%	-0.5%	5.0%	-5.0%	7.4%	4.6%	0.6%	1.5%	15.76
Explained gap	3.92	5.7%	-0.3%	5.3%	-5.3%	7.4%	4.1%	0.8%	1.5%	12.59
Initial human capital (*y*)	2.45	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	6.51
Matching efficiency (*A*)	-0.09	-0.7%	0.2%	-0.6%	0.6%	-0.9%	-0.3%	-1.9%	-0.6%	-0.37
Search effort, nonparticipants (ψ)	0.07	1.3%	0.0%	1.3%	-1.3%	-1.1%	1.7%	-0.4%	1.4%	0.66
Returns to experience (r)	0.96	0.6%	-0.1%	0.5%	-0.5%	4.7%	1.3%	1.6%	0.4%	3.36
Separation rate to unempl. (π_{EU})	0.16	1.0%	-0.5%	0.5%	-0.5%	1.4%	0.4%	0.4%	0.1%	0.57
Separation rate to non-p. (π_{EN})	0.34	3.4%	-0.2%	3.2%	-3.2%	4.3%	1.2%	1.5%	0.3%	1.75
Flow unempl. to non-p. (π_{UN})	0.03	0.0%	0.2%	0.1%	-0.1%	-0.9%	-0.3%	-0.3%	-0.1%	0.03
Flow non-p. to unempl. (π_{NU})	0.00	0.1%	0.1%	0.2%	-0.2%	-0.2%	0.0%	-0.1%	0.0%	0.06
Initial distribution of pop. (m_0)	0.00	0.1%	0.0%	0.1%	-0.1%	0.0%	0.0%	0.0%	0.0%	0.02
μ	0.38	1.0%	-0.1%	0.8%	-0.8%	6.3%	2.0%	2.1%	0.7%	2.02

Absolute contributions

	Wage	Empl	Unemp	Part	Non-part	θ^U	θ^N	π_{UE}	π_{NE}	W
Human capital										
Initial human capital (*y*)	59.8%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	48.8%
Returns to experience (*r*)	23.5%	8.5%	-8.5%	7.7%	-7.7%	34.9%	24.4%	25.9%	13.8%	25.2%
Matching efficiency										
Matching efficiency (*A*)	-2.1%	-10.2%	13.6%	-8.9%	8.9%	-6.6%	-5.9%	-30.4%	-21.1%	-2.8%
Search effort, nonparticipants (ψ)	1.7%	17.7%	-0.3%	19.8%	-19.8%	-8.1%	32.9%	-6.0%	46.8%	4.9%
Separation rates (d)										
To unemployment (π_{EU})	3.9%	13.5%	-40.5%	7.3%	-7.3%	10.4%	7.5%	7.0%	3.5%	4.3%
To nonparticipation (π_{EN})	8.2%	47.0%	-13.8%	49.7%	-49.7%	32.0%	23.0%	23.6%	10.4%	13.1%
Others										
π_{UN}	0.6%	-0.4%	13.9%	2.3%	-2.3%	-6.5%	-5.6%	-4.8%	-3.4%	0.2%
π_{UN}	0.1%	1.5%	8.8%	3.3%	-3.3%	-1.6%	0.6%	-2.2%	1.1%	0.4%
m_0	0.1%	1.3%	-0.5%	1.0%	-1.0%	0.0%	-0.2%	0.0%	0.0%	0.1%
Sum absolute contributions	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Statistical discrimination										
Total contribution	9.3%	13.4%	-11.0%	12.9%	-12.9%	46.7%	38.2%	34.2%	22.4%	15.2%
As share of d	76.7%	22.1%	20.2%	22.6%	22.6%	110.3%	125.3%	111.6%	161.6%	86.9%

Notes: This table displays the contributions of each variable in generating the skill gap in labor market outcomes. The skill gap in each outcome is calculated as a difference between the population-weighted average outcome of all skilled individuals and the population-weighted average outcome of all unskilled individuals. For example, the average gap in hourly wage rate (Wage) between the skilled and the unskilled is observed to be \$4.73 in the data. The summed up contribution of the individual model variables equals \$3.92 (Explained gap), while the remaining part of the wage gap arises from the correlations between individual variables.

Table D3.4: Detailed decomposition of the race gaps

	Wage	Empl	Unemp	Part	Non-part	θ^U	θ^N	π_{UE}	π_{NE}	W
Average gap (weighted)	1.29	1.7%	-0.6%	1.2%	-1.2%	7.5%	-0.4%	1.7%	-1.3%	4.24
Explained gap	1.20	1.6%	-0.5%	1.0%	-1.0%	6.5%	-0.2%	1.6%	-1.2%	3.96
Initial human capital (*y*)	0.34	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.93
Matching efficiency (*A*)	0.00	-0.2%	0.1%	-0.1%	0.1%	-0.2%	0.1%	-0.8%	0.0%	0.07
Search effort, nonparticipants (ψ)	-0.09	-1.5%	0.0%	-1.5%	1.5%	1.3%	-2.0%	0.5%	-1.6%	-0.79
Returns to experience (r)	0.51	0.2%	0.0%	0.2%	-0.2%	1.7%	0.6%	0.6%	0.2%	1.78
Separation rate to unempl. (π_{EU})	0.12	0.7%	-0.4%	0.3%	-0.3%	0.9%	0.3%	0.3%	0.1%	0.48
Separation rate to non-p. (π_{EN})	0.31	2.4%	-0.1%	2.2%	-2.2%	2.9%	0.9%	1.0%	0.2%	1.51
Flow unempl. to non-p. (π_{UN})	0.02	0.0%	0.1%	0.1%	-0.1%	-0.4%	-0.2%	-0.2%	-0.1%	0.03
Flow non-p. to unempl. (π_{NU})	-0.01	-0.1%	-0.2%	-0.3%	0.3%	0.3%	0.0%	0.1%	0.0%	-0.06
Initial distribution of pop. (m_0)	0.00	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.02
μ	0.32	0.7%	-0.1%	0.6%	-0.6%	4.1%	1.7%	1.4%	0.5%	1.74

Absolute contributions

	Wage	Empl	Unemp	Part	Non-part	θ^U	θ^N	π_{UE}	π_{NE}	W
Human capital										
Initial human capital (*y*)	24.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	16.5%
Returns to experience (*r*)	36.5%	4.5%	4.9%	3.7%	3.7%	22.3%	-14.8%	17.4%	-8.9%	31.4%
Matching efficiency										
Matching efficiency (*A*)	0.2%	-3.1%	-7.5%	-1.9%	-1.9%	-2.4%	-3.1%	-22.2%	1.0%	1.3%
Search effort, nonparticipants (ψ)	-6.7%	-29.3%	-2.9%	-30.8%	-30.8%	17.5%	46.9%	13.5%	73.7%	-14.0%
Separation rates (d)										
To unemployment (π_{EU})	8.5%	13.3%	36.8%	6.6%	6.6%	11.6%	-7.8%	9.2%	-4.9%	8.4%
To nonparticipation (π_{EN})	21.9%	46.7%	13.8%	47.3%	47.3%	37.1%	-21.2%	28.4%	-7.8%	26.6%
Others										
π_{UN}	1.2%	-0.2%	-13.3%	2.5%	2.5%	-5.5%	4.8%	-5.1%	3.0%	0.5%
π_{UN}	-0.4%	-1.9%	20.3%	-6.4%	-6.4%	3.5%	-1.1%	4.2%	-0.5%	-1.0%
m_0	0.3%	0.9%	0.7%	0.8%	0.8%	0.0%	0.3%	0.0%	0.2%	0.3%
Sum absolute contributions	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Statistical discrimination										
Total contribution	22.6%	13.7%	11.7%	12.6%	12.6%	53.5%	-38.5%	40.7%	-24.6%	30.7%
As share of d	74.4%	22.9%	23.1%	23.4%	23.4%	109.7%	132.9%	108.1%	194.0%	87.4%

Notes: This table displays the contributions of each variable in generating the race gap in labor market outcomes. The race gap in each outcome is calculated as a difference between the population-weighted average outcome of Whites and the population-weighted average outcome of minorities. For example, the average gap in hourly wage rate (Wage) between Whites and minorities is observed to be \$1.32 in the data. The summed up contribution of the individual model variables equals \$1.23 (Explained gap), while the remaining part of the wage gap arises from the correlations between individual variables.