Equilibrium Unemployment: The Role Of Discrimination

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Keywords
Search, Unemployment, Discrimination, Statistical Discrimination, Taste-Based Discrimination, Structural, Decomposition

Disciplines
Demography, Population, and Ecology | Inequality and Stratification | Labor Economics

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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/ethnicities, educational groups and age. In the spirit of Chari, Kehoe, and McGrattan (2007), we use a structural model approach to decompose the observed differences in labor market outcomes across demographic groups in terms of underlying wedges, or frictions. Of particular interest is the potential role of discrimination, either taste-based or statistical. Our prototype model is a version of the Diamond-Mortensen-Pissarides model extended to include a life cycle, learning by doing, a non-participation state, and informational frictions. The prototype exhibits group-specific wedges in initial human capital, returns to experience, matching efficiencies, and hazard rates. We use the model to reverse engineer group-specific wedges which 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 reveals that differences in initial human capital, returns to experience, and in hazard 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.

JEL: E2, J6, J7

The U.S. population has grown increasingly diverse during the last 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, and those differences constitute an important dimension of economic inequality (Altonji & Blank 1999, Guryan and Charles 2012, Lang and Lehmann 2012, Blau and Kahn 2017, Cajner et. al. 2017). Figure 2 uses data from the Current Population

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Figure 1: Composition of the U.S. Population: 1980-2060 (Census and Census Projections)

Survey (CPS) for the period 1998-2018 to illustrate some of these inequities. The figure includes eight demographic groups and four labor market outcomes: wages, unemployment, non-participation, and job-finding rates.\(^1\)

What are the underlying sources of the observed labor market disparities among demographic groups? To what extent could these differences reflect discrimination? What is the potential aggregate cost of discrimination? This paper uses macro accounting techniques, in the spirit of Chari et al. (2007), to address these questions. The technique introduces wedges, or frictions, into a canonical, or prototype, frictionless model. Wedges are then calibrated so that the model exactly matches relevant evidence. The purpose of the exercise is not to validate the prototype. Instead, the wedges suggest dimensions along which the prototype would need to be extended. Each calibrated wedge is then fed back into the prototype to assess its quantitative importance in explaining the evidence, or its individual contribution. Accounting techniques of this type are helpful to identify the most and least promising lines of research. For example, Chari et al. use the standard growth model as their prototype, extend it to include four time-varying wedges, and calibrate them to match series of output, labor, consumption, and investment. They find that efficiency and labor wedges accounted for most of the post-war business cycles while investment wedges played only a minor role.

\(^1\)See Section 2 for details.
Pissarides (DMP) model. The DMP model is the canonical model of the labor market, provides predictions for the variables of interest, wages, job-finding, employment, and unemployment rates, and offers a unified general equilibrium framework. Furthermore, the decentralized allocation is efficient under enough segmentation and if a Hosios type of condition holds. As in Chari et. al., the prototype can be enriched by introducing proper wedges so that a calibrated version of the model can exactly match the relevant evidence, such as the one portrayed in Figure 2. Our choice of the DMP model is also consistent with Lang and Lehmann (2012) conjecture that search models with statistical discrimination may better fit the wage and employment data simultaneously.

The DMP model seeks to explain vacancy posting, unemployment, and wages in terms of underlying economic incentives and a costly matching process. 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. A role for discrimination can be present in at least two components of the model. First, “taste-based” discrimination in hiring can take the form of a wedge across groups in their matching productivity. Second, “statistical discrimination” can also 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 individ-

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2Although the DMP model has been questioned in its ability to account for unemployment fluctuations, for example by Shimer 2005, the model still remains the standard for studying the natural rate of unemployment. Our analysis can be regarded as an exploration into the determinants of unequal natural rates of unemployment among demographic groups.
uals observe group-specific statistics ($\mu = 1$) or just statistics common among
groups ($\mu = 0$). The strategy to identify $\mu$ is a novel contribution of the paper.

We further extend the standard DMP framework along the following lines.
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. Nonparticipants
are allowed to search for jobs in the model to match the observed flows from
non-participation to employment, but unemployed and nonparticipating workers
differ in their search intensities. We also 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 in finite time. This
feature allows us to study the labor market outcomes over the life cycle, and
life-cycle patterns of potential discrimination.

We allow for human capital accumulation through learning-by-doing. Employed workers gain experience, which enhances their human capital. Being a
non-employed, either an unemployed or a non-participant, is costly since experience and human capital stay constant. This is an important channel to consider
because labor market attachment is very different for different 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. We allow labor markets to be segmented by demographic groups – defined by gender and race/ethnicity but also by age, experience, and education
– in order to properly account for the observed degree of labor market disparities, particularly differences in job-finding rates. Segmentation by itself does
not create discrimination but it makes it feasible. In particular, workers with
similar characteristics facing non-discriminatory employers should display similar labor market outcomes, even if markets are segmented. In the same vein,
workers with intrinsically different fundamental characteristics should exhibit
different outcomes.

The main task of the 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, through the lenses of the DMP model. We include all the
major demographic groups in the U.S. labor market in our analysis: females
and males (gender), Asians, Blacks, Hispanics, and Whites (race/ethnicity),
and college and non-college educated (education). The core of the paper is
the calibration of the fundamental parameters and the counterfactual exercises
assessing the role of different wedges in accounting for labor market disparities.

The spirit of the quantitative exercise is to let the data speak for itself through
the lenses of the DMP model. As in Chari et. al. (2007), we reverse engineer
the underlying parameters, and in particular implied parametric wedges among
demographic groups, needed to exactly match a number of targets for the various
groups during the 1998-2018 period. Specifically, given estimated job separation
rates, or hazard rates, and flows between unemployment and non-participation, we use the model to calculate group-specific initial levels of human capital, age-specific returns to experience, and matching productivities for the unemployed and the nonparticipants required to exactly match stylized life-cycle patterns of wages and job-finding rates for various demographic groups. The key parameter $\mu$ is calibrated so that the white/black male ratio of vacancies per unemployed worker, or tightness rate, is 1.5 consistent with the findings of Bertrand and Mullainathan (2004) regarding callback rates.

Parametric wedges, relative to a reference group, can then be calculated for (i) initial human capitals; (ii) returns to experience; (iii) matching productivities for the unemployed and non-participants; and (iv) separation rates. The extent to which each wedge accounts for observed disparities in wages, employment, earnings, finding rates, and other labor market outcomes, is then assessed through counterfactual exercises of closing one wedge at a time. Wedges (i) and (ii) refer explicitly to differences in the human capital of the worker and can be regarded as wedges in “fundamentals.” Wedges (iii) and (iv) are “search frictions” wedges and may include elements of “taste-based” and “statistical” discrimination.

The following are the main results of the paper.

1. Our calibrated human capital series differ significantly between demographic groups. Differences start relatively small, at age 25, and widen over the life cycle. Our estimates are roughly consistent with existing estimates in the literature, particularly with Oaxaca-Blinder decompositions (see Blau and Kahn 2017 for a literature review for the case of gender gaps). Consistently with this literature, we find a potential role for discrimination embedded in the different calibrated returns to education and returns to experience across demographic groups. But we find that human capital differences alone cannot explain differences in key labor market outcomes. Additional wedges in search frictions, specifically in matching productivities and/or statistical discrimination, are required for the model to be able to match the differential finding and unemployment rates.

2. A version of the model without statistical discrimination can match the wage and employment/unemployment data. Such a version would require substantial wedges in matching productivities and human capital. Those wedges would be consistent with significant taste-based discrimination in hiring and promotions. However, the implied tightness rates would be relatively similar across demographic groups.

3. Requiring the white/black male ratio of vacancies per unemployed worker to be 1.5, consistent with the findings of Bertrand and Mullainathan (2004) regarding callbacks for interviews, implies that only the version with full statistical discrimination can match this target. When firms can observe and use group-specific statistics, particularly separation rates, then a worker belonging to a group with less market attachment is less valuable to the firm. As a result, firms post fewer vacancies for those type of workers. The model with statistical discrimination naturally predicts a vacancy gap between Black and White workers induced by the higher separation rates of the former. This gap narrows when
statistical discrimination weakens. In this version of the model, our preferred version, the need for wedges in matching productivities, and the potential role for taste-based discrimination is significantly downplayed, on average, although it remains important for certain groups and certain outcomes, such as for the finding rates of Black males and Asian females.

4. According to the calibrated model, human capital differences account for around 50% of the average gap in lifetime earnings, including all groups, search frictions account for around 25%, and the remaining 25% is accounted for by interactions between the two. These figures are consistent with other estimates in the literature. Around 24% of the average gap is accounted for by statistical discrimination.

5. We separately decompose skill gaps, or skill premiums, gender gaps, and race/ethnic gaps. Regarding the average gaps in lifetime earnings, we find that: wedges in human capital variables account for 74% of the skill gap; 45% of the gender gaps; and 47% of the average racial/ethnic gap. Statistical discrimination accounts for 15.2% of the skill gaps; 25% of the gender gap; and 31% of the racial/ethnic gap in lifetime earnings. The majority of the wage gaps can be explained by the differences in human capital. However, the wedges in human capital variables can explain only a fairly small part of the employment gaps. Search frictions account for most of the gaps, in particular wedges in separation rates. Statistical discrimination accounts for between 10 to 15% of the employment gaps.

6. We find that there are significant differences in matching productivities 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 labor market outcomes.

7. Wedges in job separation rates, particularly to non-participation, explain a large fraction of the gaps in employment, wages, job-finding rates, life-cycle welfare, and GDP. The role of match breaks into non-participation is larger for gender gaps, but it is also quantitatively important for racial gaps in a variety of labor outcomes.

8. Our model can explain Goldin (2014, pg 1097) puzzle regarding why the gender gap in earnings increases over the life-cycle but closes after age 40. A similar pattern is observed for race/ethnic gaps. According to our model, this pattern is explained to a large extent by the pattern of separation rates, which are higher for females in their 20’s and 30’s, but more similar to that of males after age 40. In the presence of statistical discrimination, such a pattern strongly influences labor market outcomes such as earnings.

9. The matching efficiency disproportionally falls at the end of the life cycle for Hispanic and Asian males, and to some degree for Black males, suggesting potential taste-based discrimination for older minority male groups.

There are two main theories of discrimination: taste-based discrimination, pioneered by Becker (1957), and statistical discrimination, pioneered by Arrow (1973) and Phelps (1972). Our findings suggest that statistical discrimination
is potentially a more important source of discrimination than prejudice. This conclusion is consistent with a variety of micro evidence including List (2004), Levit (2004), and Ewens et al. (2014). Lang and Lehmann (2002) 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” (pg 970). We find a quantitatively small role for prejudice, and a large potential role for statistical discrimination, based on the finding that the pure taste-based discrimination model cannot generate sufficient differences in Black-White tightness rates, as suggested by the callbacks evidence obtained by Bertrand and Mullainathan (2004), while the model with full statistical discrimination can.

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 Coate and Loury (1995), Rosen (1997), More and Norman (2004), Gayle and Golan (2012), or Jarosch and Pilosof (2019) among others, 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 6.

The remainder of the paper is organized as follows. Section 2 presents the model, Section 3 explains the calibration strategy, Section 4 reports the calibration and decomposition results, Section 5 reports robustness checks, Section 6 provides a literature review, and Section 6 concludes.

1 Model

Consider a version of the Diamond-Mortensen-Pissarides (DMP) model extended to include heterogeneous workers and segmented labor markets. The extended model also features a life-cycle with finite horizon, learning-by-doing, and a non-participation state. Time is discrete and age is denoted by $a$ where $a \in \mathbb{A} \equiv [\underline{a}, \overline{a}]$. The focus of the model is on working years, after schooling and education has been completed and before retirement.

1.1 Set Up

Workers. Individuals enter the labor market at age $\underline{a}$, retire at age $a_R$, and die at age $\overline{a}$ where $\overline{a} > a_R$. We call non-retired individuals workers. At any point in time worker are either employed, $E$, unemployed, $U$, or nonparticipants, $N$. Let $s \in S \equiv \{E, U, N\}$ denote the employment status of a worker. Individuals enter the labor market with no experience and gain experience through employment. Let $e \in [0, \overline{a} - \underline{a}]$ denote years of experience. Each period of employment increases experience by one, $e_{a+1} = e_a + 1$, and each non-working period keeps experience constant, $e_{a+1} = e_a$. Individuals also belong to a demographic
group \( i \) defined by gender (female, male), race and/or ethnicity (Asian, Black, Hispanic, or non-Hispanic White), and education level (skilled, unskilled). For example, \( i \) could refer to an skilled Black female. Let \( I \) denote the set of demographic groups. A worker is fully identified by her/his years of experience \( e \), age \( a \), labor status \( s \), and demographic group \( i \). Denote by \( x = (e, a, s, i) \) the state, or type, of a worker where \( x \in [0, a - 1] \times [a, aR] \times S \times I \) and let \( x' = (e + 1, a + 1, s, i) \). The state of a retiree is defined as \( x_R = (e, aR, \bar{N}, i) \). It is useful to define \( g_i^e (e, a) \equiv g_i (e, a, s) \equiv g(x) \) which provides three ways to write the same expression. Furthermore, whenever employment status is obvious, we just write \( g_i (e, a) \).

Let \( m(x) \) the mass of workers of type \( x \). The initial mass distribution, \( m_i^s (0, a) \) is given for all \( s \) and \( i \). Workers transition into unemployment and non-participation at exogenous rates \( \pi_{EU} (x) \), \( \pi_{EN} (x) \), \( \pi_{UN} (x) \), and \( \pi_{NU} (x) \), and into employment at endogenous rates \( \pi_{NE} (x) \) and \( \pi_{UE} (x) \). Let \( c(x) \) and \( w(x) \) denote consumption and wage of type \( x \). Workers seek to maximize their expected present value of consumption. They are risk neutral and discount the future according to the discount factor \( \beta \in (0, 1) \). There are no savings so that \( c(x) = w(x) \) for employed workers. Wages of employed workers are determined by Nash-bargaining with employers while wages, or consumption, of non-employed workers and retirees are given by \( c(x) \), an exogenous parametric form. For completeness, it is convenient to define \( \tau^E_i (e, a) = \tau^U_i (e, a) \) which would allow for a concise notation when describing the solution for wages. For simplicity, we do not explicitly describe the domain of each function whenever is clear. For example, \( w(x) \) refers to employed workers only, \( x = (e, a, \bar{E}, i) \). \(^3\)

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:

\[
h(x) = y_i \exp (r(x) e),
\]

where \( y_i \) is a baseline, or entering, level of human capital associated to group \( i \) while \( r(x) \) is a type-specific returns to experience. Both \( y_i \) and \( r(x) \) are exogenous. We also refer to \( y_i \) as educational human capital, the human capital of a new worker for whom \( e = 0 \). Differences in baseline productivity, \( y_i \), and returns to experience, \( r(x) \), across types could capture differences in the quality and quantity of education among 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 \( x \).

Our formulation assumes that post-schooling human capital formation is of the learning-by-doing type as in Barlevy (2008), Yamaguchi (2010) and Bagger et. al. (2014). An alternative formulation, for example of the Ben-Porath form, is possible. However, Heckman et. al. (2002) argue that it is difficult

\(^3\)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 thus on determining employment/unemployment rates, wages, finding- and tightness-rates for all type of workers, as defined by \( x \). For example, the job finding rate of a 45 year-old non-participant skilled Black female with 10 years of experience.
to distinguish between learning-by-doing and on-the-job training based on the empirical evidence.

**Firms and labor markets**: There is a continuum of infinitely-lived firms who 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’s types. Firms can freely enter in any of the segmented markets. Firms post vacancies for long-term positions at a cost of \( \kappa(x) \) per vacancy, a cost that may depend on worker’s type. A successful match produces \( h(x) \) units of output per-period while gross per-period profits are \( h(x) - w(x) \). A match is destroyed exogenously at the rate \( d(x) \).

The assumption of segmented market requires some discussion. First, segmentation is needed in order for the model to match key features of the data such as differential job-finding rates among demographic groups, as we will show. Second, segmentation across race, gender, ethnicity and age may be unlawful, as it may violate the Civil Rights Act and/or the Employment Act for example. However, discriminatory behavior is hard to prove in practice. The evidence suggests that anti-discriminatory laws have had limited success (Valfort 2018). Third, segmentation by itself does not create discrimination although it makes it feasible. In particular, workers with similar characteristics facing non-discriminatory employers should display similar labor market outcomes even if markets are segmented. Fourth, in the absence of discrimination, segmentation would be required for allocations to be efficient. On that regard, we would need even more segmentation than what we are allowing.

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

\[
u(x) = \begin{cases} 
  m(x), & \text{if } s = U, \\
  \psi(x) m(x), & \text{if } s = N, \\
  0 & \text{otherwise}. 
\end{cases}
\]  

We assume that the matching technology adopts a standard Cobb-Douglas form \( M(u, v; x) = A(x) u^\alpha v^{(1-\alpha)} \) where \( A(x) \) represents the efficiency of the matching technology and it is allowed to depend on workers’ type. Differences in matching efficiency across types reflect search frictions associated to 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 \( \phi(x) \).

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4As noted by Lang and Lehmann (2012, pg 970), almost all models they review implicitly assume such illegal practices.

5Job to job search are suboptimal in the model given that there is no expected gain from a match break.
Let $\theta(x) = \frac{v(x)}{u(x)}$ 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 $q(x) = M(u(x), v(x); x) / v(x) = A(x)(\theta(x))^{-\alpha}$, and a non-employed worker’s probability of finding a job is $f(x) = M(u(x), v(x); x) / u(x) = A(x)(\theta(x))^{1-\alpha}$. These expressions make clear that finding rates are sole functions of job tightness rates and the efficiencies of the matching function.

The following assumption will guarantee that matches generate a strictly positive surplus.

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

This first part of the assumption is standard. The second part reinforces the benefit of remaining in a match as it (weakly) increases pensions. Otherwise, $h(x) > \bar{c}(x)$ may not be sufficient to guarantee that a match generates a positive surplus.

**Statistical discrimination**: The notion that employers use statistics specific to a demographic group when assessing individual’s prospects is present in the model through the destruction rates $d(x)$. Specifically, firms in a given market $x$ can perfectly forecast the human capital of the worker they are looking to hire, but the expected duration of the match depends on job separation rates, $d(x)$, specific to that market. Statistical discrimination arises if $d(x)$ is a function of $i$, the demographic identifier. To assess the extent to which statistical discrimination is prevalent in labor markets, at the light of the model, we assume that firms and workers only observe a noisy signal of the true job destruction rate of group $x$. While the true job destruction rate is $\tilde{d}(x) = \bar{\pi}_{EU}(x) + \bar{\pi}_{EN}(x)$, firms and workers observe $d(x) = \mu \tilde{d}(x) + (1 - \mu) \bar{d}(x)$ where $\mu \in [0, 1]$ is a parameter and $\bar{d}(x)$ is a reference, or baseline, destruction rate common among all groups. For example, $\bar{d}(x)$ could be the average destruction rate across demographic groups or it could be the job destruction rate of a reference group such as White males. On the one extreme, if $\mu = 1$ then firms are able to perfectly (statistically) discriminate when posting vacancies and negotiating wages by using group-specific average separation rates. On the other extreme, if $\mu = 0$ firms can only use destruction rates common for all demographic groups.

Similarly for workers. They observe $\pi_{EU}(x) = \mu \bar{\pi}_{EU}(x) + (1 - \mu) \tilde{\pi}_{EU}(x)$ and $\pi_{EN}(x) = \mu \bar{\pi}_{EN}(x) + (1 - \mu) \tilde{\pi}_{EN}(x)$ where $\tilde{\pi}_{EU}(x)$ and $\tilde{\pi}_{EU}(x)$ are defined analogously to $\tilde{d}(x)$. Parameter $\mu$ will be calibrated.\(^6\)

**Gaps and taste-based discrimination**: Before moving into the details of the model, it is convenient to briefly explain the main goal of the paper at the light of the set up just described. We use the model’s solution to calibrate and/or reverse engineering some of the parameters of the model such as $\mu$, $y_t$, $r(x)$, $\kappa(x)$, $A(x)$, $\phi(x)$, and/or $\psi(x)$. Reverse engineering is a step further

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\(^6\)1 - $\mu$ could be interpreted as the degree of 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 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.
from calibration in the sense that it seeks to match complete sequences of wages and finding rates of different groups over the entire life-cycle, not only some selected moments or stylized facts. The result are then used to calculate and interpret gaps in parameters across gender, race/ethnicity, age and education. Finally, counterfactual exercises are performed. The calibrated gaps represent the underlying fundamental sources of unequal labor market outcomes among demographic groups, according to the model. By separating human capital from other forces, 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 parameters $\kappa(x)$, $A(x)$ and/or $\psi(x)$, while taste-based discrimination during employment could be linked to gaps in parameters $r(x)$ and/or $\phi(x)$.

### 1.2 Recursive formulation

#### 1.2.1 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 an employed worker of type $x = [e, a, \bar{E}, i]$. Then

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

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 the value of posting a new vacancy, $\bar{V}$, if the match is destroyed, which occurs with a probability $d(x)$, and the value of remaining in the match, $J_i(e + 1, a + 1)$, which occurs with a 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 with no workers 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:

$$\bar{V} = \max_x \{ V(x), 0 \}.$$  

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 $\bar{V} = 0$ as well. Active firms are thus indifferent in which type of a worker to hire and in which segmented market to operate as long as the free entry condition holds.\footnote{Prejudicial employers may still operate in markets they despise if, for example, negotiated wages in that market are sufficiently low as to break even.}
The problem of firm with a worker then simplifies to

\[
J(x) = \begin{cases} 
  h(x) - w(x) + \beta (1 - d(x)) J(x') & \text{if } a \leq a < a_R - 1, \\
  h(x) - w(x) & \text{if } a = a_R - 1
\end{cases}
\]

while for firms posting vacancies

\[
\kappa(x) = \beta q(x) J_i(e, a + 1) = \beta f(x) \theta(x)^{-1} J_i(e, a + 1) \text{ for } a \leq a < a_R - 1.
\]

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.

### 1.2.2 An individual’s problem

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

\[
R(x_R) = \sum_{i=a_R}^{\pi} \beta^{i-a_R} \pi(x_R) = \frac{1 - \beta^{a_R-1}}{1 - \beta} \pi(x_R).
\]

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:

\[
E(x) = \begin{cases} 
  w(x) + \beta \left[ \pi_{EU}(x) U(x') + \pi_{EN}(x) N(x') \right] & \text{if } a \leq a < a_R - 1 \\
  w(x) + \beta R_i(e + 1, a_R, N) & \text{if } a = a_R - 1
\end{cases},
\]

\[
U(x) = \begin{cases} 
  \bar{\pi}(x) + \beta \left[ f(x) E_i(e, a + 1) + \bar{\pi}_{UN}(x) N_i(e, a + 1) \right] & \text{if } a \leq a < a_R - 1 \\
  \bar{\pi}(x) + \beta R_i(e, a_R, N) & \text{if } a = a_R - 1
\end{cases},
\]

\[
N(x) = \begin{cases} 
  \bar{\pi}(x) + \beta \left[ f(x) E_i(e, a + 1) + \bar{\pi}_{NU}(x) U_i(e, a + 1) \right] & \text{if } a \leq a < a_R - 1 \\
  \bar{\pi}(x) + \beta R_i(e, a_R, N) & \text{if } a = a_R - 1
\end{cases},
\]

The interpretation of these functionals is intuitive. An employed worker consumes his/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 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 $\tau(x) = \tau_i(e, a, \bar{U})$ during unemployment. Next period, he may find a job with probability $f(x) = f_i(e, a, \bar{U})$ in which case he moves to the employment state. He may also move to non-participation with probability $\bar{\pi}_{UN}(x)$, and otherwise he will stay unemployed. Similarly for a nonparticipating worker.

It is convenient to define the average utility of individual $x$ as:

$$W(x) = m_i^E(e, a) E(x) + m_i^U(e, a) U(x) + m_i^N(e, a) N(x).$$  \hfill (9)

1.2.3 Nash bargaining

Wages in the model are negotiated through Nash bargaining. Firms and workers 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:

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

The solution for each labor market satisfies:

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

1.3 Aggregate labor flows

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

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

---

8We assume that the outside option for a worker during bargaining is always unemployment, $U$. An alternative specification is to allow the outside option of the worker to be non-participation, or a mix between both. As discussed in Cordoba et al. (2020), efficiency requires the surplus of a new worker to be defined relative to the worker's previous state, before becoming employed, either unemployed or non-participation. But efficiency does not restrict how the surplus is divided for workers with tenure in the job. For tractability, we assume a simple outside option, unemployment. This reduces the vector $x$ but also implies that allocations are not fully efficient. We provide a robustness check of using non-participation as the outside option.
Moreover, the mass of individuals with experience \( e \in [1, a] \) at age \( a \in [a, a_R - 2] \) satisfies:

\[
m^E_i(e, a + 1) = (1 - \pi_{EU}(x) - \pi_{EN}(x)) \times m^E_i(e - 1, a) + f^U_i(e, a) \times m^U_i(e, a) + f^N_i(e, a) \times m^N_i(e, a);
\]
\[
m^U_i(e, a + 1) = (1 - \pi_{UN}(x) - \pi_{NU}(x)) \times m^U_i(e, a) + \pi_{NU}(x) \times m^U_i(e, a) + \pi_{EN}(x) \times m^N_i(e, a) + \pi_{EU}(x) \times m^E_i(e - 1, a);
\]
\[
m^N_i(e, a + 1) = (1 - \pi_{NU}(x) - \pi_{UN}(x)) \times m^N_i(e, a) + \pi_{UN}(x) \times m^U_i(e, a) + \pi_{EU}(x) \times m^E_i(e - 1, a).
\]

Notice that while the firms and the workers may not be sure about the accurate match break probabilities, \( \pi_{EU} \) and \( \pi_{EN} \), the actual flows into employment, unemployment, and non-participation evolve according to the actual probabilities.

### 1.4 Characterization of the solution

We now provide some characterization of the solution for wages, tightness rates and job-finding rates using backward induction. In particular, closed-form solutions for the last period of working life are obtained and then used to find solutions for the previous periods.

#### 1.4.1 Solution for \( a = a_R - 1 \)

Workers work until age \( a_R - 1 \). Denote by \( x_{R-1} = (e, a_R - 1, E, i) \) the final state of a worker, just before retirement. Using (3), (6) and (7), the Nash Bargaining solution (10) for a terminal state simplifies to:

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

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

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

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

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

\[
J(x_{R-1}) = (1 - \phi(x_{R-1})) \left[h(x_{R-1}) - \bar{c}^U_i(e, a_R - 1) + \beta \Delta R_i(e + 1, a_R)\right].
\]
The terminal value of the firm is a fraction of the surplus of the match which includes production plus added retirement funds minus unemployed consumption. Assumption 1 guarantees that \( J(x_{R-1}) \) is positive. The terminal value of the firm can be used to determine the terminal job tightness ratio which occurs at age \( a_R - 2 \). According to (4) and the definition of \( q(x) \):

\[
\theta^*_t (e, a_R - 2) = \frac{v^*_t (e, a_R - 2)}{u^*_t (e, a_R - 2)} = \left[ \frac{\beta A_t (e, a_R - 2, s)}{\kappa_t (e, a_R - 2, s)} J(x_{R-1}) \right]^{1/\alpha}.
\]  (15)

This expression, together with (14), shows that vacancies are more abundant for workers with higher human capital, lower outside consumption and/or in more efficient labor markets characterized by a higher \( A \) and/or a lower \( \kappa \). The model predicts, for example, more open vacancies for experienced workers and immigrants with lower outside options, all else equal. The terminal job finding rate can be solved as

\[
f^*_t (e, a_R - 2)^\alpha = \frac{A_t (e, a_R - 2, s)}{\kappa_t (e, a_R - 2, s)} (J(x_{R-1}))^{1-\alpha}.
\]  (16)

Job-finding rates are higher in markets with more efficient matching, lower costs of posting vacancies, and/or higher value for active firms.

1.4.2 Solution for \( a < a_R - 1 \)

The solutions for other periods can be expressed in terms of workers’ surpluses and/or value changes defined as:

\[
S_{EU} (x) \equiv E(x) - U(x) (e, a); \quad S_{EN} (x) \equiv E(x) - \bar{N}(x) (e, a); \quad (17)
\]

\[
S_{NU} (x) \equiv N(x) - U(x) (e, a); \quad S_{UN} (x) \equiv U(x) - \bar{N}(x) (e, a); \quad \Delta U(x) \equiv U(x) - U_i (e - 1, a); \quad \Delta \bar{N}(x) = N(e, a) - N_i (e - 1, a).
\]

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:

\[
w(x) = \frac{h (x) + \Theta (x) [\bar{c} (x) + \beta \Omega (x)]}{1 + \Theta (x)}, \quad (18)
\]

\[
\theta (x) = \left[ \frac{\beta A (x) J_i (e, a + 1)}{\kappa (x)} \right]^{1/\alpha}, \quad \text{and} \quad (19)
\]

\[
f(x)^\alpha = \frac{A(x)}{\kappa (x)^{1-\alpha}} (\beta J_i (e, a + 1))^{1-\alpha}, \quad \text{where} \quad (20)
\]

\[
\Omega (x) = f^U_i (e, a) S^i_{EU} (e, a + 1) + \bar{\pi}_{EU} (x) S^i_{NU} (e, a + 1) + \pi_{EU} (x) [S^i_{EN} (x') - S^i_{EU} (x')] - \Delta U (e + 1, a + 1), \quad (21)
\]

\[
J_i (e, a + 1) = \Theta (x) S^i_{EU} (e, a + 1), \quad \text{and}
\]

15
\[ S_{EU} (x) = w(x) - c_i^U (e, a) + \beta \begin{bmatrix} (1 - \pi_{EU}(x)) S_{EU} (x') - \pi_{EN}(x) S_{EN} (x') \\ -\tilde{\pi}_{NU} (x) S_{NU} (e, a + 1) \\ -f_i^U (e, a) S_{EU} (e, a + 1) + \Delta U (x') \end{bmatrix} \]

**Proof.** See Appendix B.

The expression for wages, equation (18), generalizes (13). The term \( \beta \Omega(x) \) collects all "net" losses of remaining employed. Wages increase with \( \Omega(x) \) to compensate workers for those losses to an extent determined by the bargaining power. In particular, a higher job finding probability, \( f_i^U \), increases wages since \( S_{EU}^1 (e, a + 1) > 0 \). Intuitively, the higher the chances of finding a new job the higher the losses associated to remaining in the current job. Furthermore, wage equal human capital if \( \Theta(x) = 0 \) while in the other extreme wage equal \( c_i^U (e, a) + \beta \Omega(x) \) 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 \( c_i^U (e, a) + \beta \Omega(x) \), are paid more. unequal pay for equal job, the idea that \( w(x_A) \neq w(x_B) \) even when \( h(x_A) = h(x_B) \), arises naturally into the model due to search frictions.

Equation (20) shows that finding rates are a direct function of the economic value of the worker to the firm, \( J_i(e, a + 1) \). Discrimination in hiring could arise through the term \( \frac{A(x)}{\Omega(x)} \): a particularly low matching efficiency for type \( x \) workers or an unusually high cost of hiring type \( x \) workers would lead to 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 of statistical discrimination can also be gauged from these expressions. Consider the effect of \( \pi_{EU}(x) \) on wages and finding rates. For a given sequence of wages, inspection of the formulas reveal 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 incentives to post vacancies for those type of workers. Lower surpluses also lower the sequence of wages, according to (18), 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 \( x_{R-2} = x(e, a_R - 2, E, i) \). First, using the solutions already obtained for \( a = a_R - 1 \), the following results can be found:

\[
\begin{align*}
S_{EU} (x_{R-1}) &= w(x_{R-1}) - c_i^U (e, a_R - 1) + \beta \Delta R_i (e + 1, a_R), \\
S_{EN} (x_{R-1}) &= w(x_{R-1}) - c_i^N (e, a_R - 1) + \beta \Delta R_i (e + 1, a_R), \\
S_{NU} (x_{R-1}) &= c_i^N (e, a_R - 1) - c_i^U (e, a_R - 1), \\
\Delta U^i (e + 1, a_R - 1) &= c_i^U (e + 1, a_R - 1) - c_i^U (e, a_R - 1) + \beta \Delta R_i (e + 1, a_R).
\end{align*}
\]
Furthermore, suppose just for illustration that \( \bar{c}(x) = \bar{c} \) for all \( x \). In that case

\[
S_{EU}(x_{R-1}) = w(x_{R-1}) - \bar{c}, \quad S_{EN}(x_{R-1}) = w(x_{R-1}) - \bar{c}, \\
S_{NU}(x_{R-1}) = 0, \quad \Delta U^i(e + 1, a_R - 1) = 0, \quad \text{and} \\
W(x_{R-2}) = f^U_i(e, a_R - 2)S_{EU}^i(e, a_R - 1).
\]

Plugging these results into (18), it follows that:

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

This expression illustrates the determination of wages, and in particular the role of the job finding rate. A higher current job finding rate tend to increase current wages unless \( \Theta(x_{R-2}) = 0 \). If \( \Theta(x_{R-2}) = 0 \) then \( w(a_{R-2}) = h(a_{R-2}) \).

On the other extreme, if \( \Theta(x_{R-2}) = \infty \) then

\[
w(x_{R-2}) = \bar{c} + \beta f^U_i(e, a_R - 2) (w(x_{R-1}) - \bar{c}),
\]

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 regressions on wages in the presence of search frictions and unemployment will not provide a correct estimate of the underlying human capital of the worker over the life-cycle. In the next section, we reverse engineer human capitals of workers in different markets over the life-cycle using the search model. As expected from the previous discussion, our estimated human capitals differ significantly from wages for certain groups.

We next calibrate the model and use it to perform a levels accounting type exercise.

2 Data

2.1 CPS Data 1998-2018

We use the basic monthly data between years 1998 and 2018 from the CPS (Current Population Survey) for both full- and part-time U.S. workers (CEPR 2019; Flood et. al. 2018). We disaggregate the data based on an individual’s race or ethnicity (Asians, Blacks, Hispanics, and Whites), gender (male, female), and education level (college, non-college, and average). In total, we investigate \( 4 \times 2 \times 3 = 24 \) different race/ethnicity-gender-education groups. To ensure that the demographic groups are mutually exclusive, we group all individuals, whose ethnicity is Hispanic, under Hispanic group, despite of their race, while we group all non-Hispanic Asians, Blacks, and Whites under corresponding racial groups.\(^9\) We divide individuals into two education groups: college, or skilled,
and non-college, or unskilled. An individual is assigned to the college group, if she/he has completed at least some college, and to the non-college group, if an individual’s highest level of completed education is high-school or less. By including the named demographic and socio-economic groups, our data consists of a representative sample of around 96 percent of the U.S. population (Census 2020).

We then calculate life-cycle patterns of average wages, employment, unemployment, and non-participation for the described demographic groups to compare various labor market outcomes between the groups. We rely on the hourly wage rates obtained from the CEPR (2019) while the other data are obtained from the raw CPS data files from IPUMS (Flood et. al. 2018). The advantage of using the CEPR wage data instead of the raw CPS data is that the CEPR adjusts the raw CPS wage data such that the constructed wage data series are consistent and comparable over time and especially suitable for research uses. We also estimate age-specific, monthly transition probabilities between employment ($E$), unemployment ($U$), and non-participation ($N$) separately for each group, following the method in Choi et. al. (2014). In practice, the transition probability estimates are weighted average flows between labor market statuses for every age, when controlling for birth cohorts. For a given cohort and survey year, we observe the fraction of individuals for a given age that transfers from one labor market status to another. Denote this variable as $\pi_{ss'}(a,c,i)$, where ss' denotes the transition from a status $s \in [E,U,N]$ to a status $s' \in [E',U',N']$, $a$ denotes an individual’s age, $c$ denotes the cohort (the birth year) an individual belongs to, and $i$ denotes the year of the survey. We obtain the estimated transition probabilities by running seemingly unrelated regressions of $\pi_{ss'}(a,c,i)$ against age dummies. The coefficient for each age dummy is the probability that a transition happens at age $a$. A limitation of the CPS data is that it does not contain a variable capturing the work experience of individuals. As a result, only average (over experience) transition probabilities can be estimated. We denote these estimated transition probabilities, $\bar{\pi}_{ss'}(e,a,s,i)$, and $\pi_{ss'}(a,s,i)$.

To remove high-frequency reversals of transitions between unemployment and non-participation, we follow the method suggested by Elsby, Hobijn, and Sahin (2015) called "deNUNification". The key idea is to correct for a possible classification error of an individual’s labor market status: an individual who move from non-participation to unemployment and back to non-participation within a short period of time is likely a nonparticipant, and including this high-frequency transitions back and forth may lead to spurious transition estimates. The correction method thus records the high-frequency transitions, NUN, as NNN. Same method is applied to high-frequency transition from unemployment to non-participation and back.

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five hundred thousands to seven hundred thousands. The numbers of observations for Asian males and females are much smaller, about three hundred thousands for each group. We exclude American Indian and Alaska Natives, Native Hawaiians and Other Pacific Islanders, and Multiracial groups from our analysis due to their small sample sizes.

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For detailed description, please refer to the CEPR-CPS documentation found in http://ceprdata.org/cps-uniform-data-extracts/cps-basic-programs/.
The estimated flows between different labor market states are flow probabilities from employment to unemployment or non-participation, \( \pi_{EU}(a,s,i) \) and \( \pi_{EN}(a,s,i) \), unemployment to non-participation, \( \pi_{UN}(a,s,i) \), non-participation to unemployment, \( \pi_{NU}(a,s,i) \), and unemployment and non-participation to employment, \( \pi_{UE}(a,s,i) \) and \( \pi_{NE}(a,s,i) \). As the time period in our model calibration will be set to a quarter instead of a month, we calculate quarterly transition probability matrices, \( \Lambda_Q(a,s,i) \), as
\[
\Lambda_Q(a,s,i) = (\Lambda_M(a,s,i))^3
\]
where
\[
\Lambda_M(a,s,i) = \begin{pmatrix}
1 - \pi_{EU}(a,s,i) - \pi_{EN}(a,s,i) \\
\pi_{UE}(a,s,i) \\
\pi_{NE}(a,s,i)
\end{pmatrix}
\begin{pmatrix}
1 - \pi_{EU}(a,s,i) - \pi_{UN}(a,s,i) \\
\pi_{UE}(a,s,i) \\
\pi_{NU}(a,s,i)
\end{pmatrix}
\begin{pmatrix}
\pi_{EN}(a,s,i) \\
\pi_{UN}(a,s,i) \\
1 - \pi_{NU}(a,s,i) - \pi_{EU}(a,s,i)
\end{pmatrix}.
\]

2.2 Stylized facts

We now highlight stylized features of the data regarding different demographic groups. Table 1 provides summary statistics of the life-cycle averages of various labor market outcomes. Figure 2, presented in the Introduction, and Figure 3 portrays corresponding average life-cycle profiles.

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

Consider next the full life-cycle profiles. Figure 2 and Figure 3 show persistent gaps over the entire life-cycle with few but important exceptions. Consider first the wage gaps in Figure 2. For each gender-race pair, life-cycle wage growth shows the well-known pattern: wages grow rapidly for young workers, the wage growth then flattens, and starts to decrease later in the career. Wages for both Asian males and 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 within-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 arises because of the higher schooling level of
<table>
<thead>
<tr>
<th>Groups</th>
<th>Pop Share</th>
<th>Wage</th>
<th>Employ. rate</th>
<th>Unemp. rate</th>
<th>Non-Part rate</th>
<th>( \pi_U )</th>
<th>( \pi_E )</th>
<th>( \pi_N )</th>
<th>( \pi_E )</th>
<th>Earnings</th>
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Table 1: Descriptive Statistics and Basic Counterfactuals (CPS 2018).

an average Asian but also from higher initial returns to school particular for Asian males.\(^{11}\) Overall, wage gaps start small, increase over the life cycle, but compress at the end of the working life.

Figure 2 also shows the average unemployment, and non-participation rates, as well as job-finding rates for the unemployed for each gender-race pair, and the following patterns are observed. 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 higher compared to Whites and Asians. Within race/ethnicity, Hispanic females have higher unemployment rates and Black females lower unemployment rates compared to males, while the unemployment rates are fairly similar for White and Asian males and females.

Figure 2 reveals variation in life-cycle non-participation rates between groups.

\(^{11}\)We were able to 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.
In general, non-participation rates are lower for younger workers, but start to increase rapidly after age 55 for all groups. Females are more likely to be non-participating over the whole life cycle and especially before age 45. Within male groups, the non-participation rates are quite similar over the whole life cycle, only exception being Black males: they are more likely to be non-participating over the whole life cycle compared to other male groups, and their non-participation rate starts to increase earlier, around age 45. In fact, the non-participation rate of Black males is closer to the non-participation rates of female groups than other male groups after age 45. It is not clear why the non-participation rate for black males differs from the rate of other male groups. An explanation could be the higher incarceration rate for black males, but as CPS data typically excludes institutionalized people, this difference cannot purely be explained because of a higher fraction of incarcerated Black males. There is more variation in the non-participation rates 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 age lower. Thus, it seems that even though Hispanics have relatively better employment outcomes compared to Blacks, their wages seem not to reflect that.

Figure 3 presents average, quarterly transition flows between employment and unemployment, and employment and non-participation for each, gender-race pair\textsuperscript{12}. 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 40-45. Overall, males tend to have higher job-finding rates compared to females, especially during the prime working years, but Black males’ job-finding rates are closer to female groups than other male groups.

When looking at the job-finding rates for the unemployed, Hispanic and White males have the highest rates over the whole life cycle compared to any other group. Between female groups, job-finding rates for unemployed follow fairly similar patterns for all minority groups while White females have the highest rates over the whole working life. While Asian females have very strong labor market outcomes in terms of wages and unemployment, their job-finding rates are surprisingly low, lowest of all the groups along with Black females.

The greatest difference between males’ and females’ job-finding rates for 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

\textsuperscript{12}As mentioned, we also estimate the transition flows separately for both education levels, which we use in the calibration.
Figure 3: Average job finding and destruction rates over the life cycle for different demographic groups (CPS 1998-2018).

and Black females have especially low job-finding rates between ages from 30 to 40. We also plot the job finding probabilities for nonparticipants, and very similar patterns are observed. A notable difference is that Black females are having the highest job finding probabilities for nonparticipants among female groups before age 45. Also, Hispanics and Asian males now have the highest job-finding rates among males, while Black and White males have almost equal rates over the life cycle. In addition, nonparticipating Asian females are significantly more likely to find jobs after age 45 when comparing to other female groups. In general, job-finding probabilities for 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 non-participation differ greatly with gender. While females are typically more likely to leave employment to non-participation, 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 race. Job destruction rates to unemployment are higher early in the life cycle, but stay relatively constant from age 35 until age 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, followed by Hispanics. Young Blacks have especially high likelihood of moving from employment to unemployment compared to any other group. Females are significantly more likely to move from employment to non-participation compared
to Asian, Hispanic, and White males. For example, young Hispanic females are about three times more likely to move to non-participation compared to Hispanic males, while White females more than twice as likely compared to White males. Also, Black males are notably more likely to move to non-participation compared to other male groups, this result being consistent with the higher non-participation rate for Black males shown in Figure 2. Black males are almost twice as likely to move from employment to non-participation during the prime working ages compared to White males, and the flows from employment to non-participation 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 non-participation over the life cycle compared to males, and Blacks have considerably higher job destruction rates compared to other races.

2.3 Skill Premium, Gender Gaps, and Racial/Ethnic Gaps

Table 1 also reports skill, gender, and race/ethnicity ratios in 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 0.6 signify that the unskilled average wage is 60% of the skilled average wage. Gender ratios similarly refers to the average of females relative to the average of males, while race/ethnic ratios refers to the average of minorities relative that of Whites. These ratios provide concise evidence of large gaps among various demographic groups in a variety of labor market outcomes. In term of average earnings, the unskilled earns 50% less than the skilled, females earns 43 percent less than males, and minorities earn 27% less than Whites. This is due gaps in both wages and employment. The unemployment rate is 50% higher for the unskilled, 22% lower for females, and 63% higher for minorities.

The last part of Table 1 reports counterfactual effects of eliminating skill, gender or race/ethnicity gaps, one by one, on the economy-wide averages of various labor market outcomes. The counterfactual of eliminating gender gaps assume that females achieve the same labor market outcomes of their male counter part of the same skill, age and race/ethnicity. The counterfactual of eliminating the race/ethnicity gap assumes that minority groups achieve the same labor market outcomes of their White counterpart of the same gender, age and skill. Finally, the counterfactual of eliminating skills gaps assume that unskilled individuals achieve the same outcomes of their skilled counterpart of the same age, gender and race/ethnicity. The potential effects of eliminating these differences are significant. For example, average earnings could increase by 27% if skills gaps were eliminated, by 20% if gender gaps were eliminated, and 11% if race/ethnicity gaps were eliminated.
3 Calibration and Reverse Engineering

3.1 Standard Parameters

We set the model 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, $m_i^s(0,a)$, is divided between employment, unemployment, and non-participation so that the values match the average values for each group $i$ observed in the CPS data between 1998–2018. We calibrate the model for 24 types of $i$: we first calibrate the model for 8 different gender (male and female) and race (Asian, Black, Hispanic, and White) groups, and then separately for 16 different gender-race-education groups, where the level of education can be either skilled or non-skilled. With skilled, we refer to everyone with at least some college education, while non-skilled group includes workers with high-school degree or less. We set the elasticity of the matching function, $\alpha$, to be equal to 0.5, a common value used in the search literature (e.g., Shimer 2005).

We adopt a simple and common formulation for the consumption while non-employed. Following Postel-Vinay and Robin (2002), Burdett et. al. (2011), and Bowles and Liu (2011) among others, we assume that consumption while non-employed is proportional to the human capital of the individual:

\[
\begin{align*}
\bar{c}(x) &= \gamma(x) \cdot h_i(x) \quad \text{for } a < a_R, \\
\bar{c}(x_R) &= \gamma^R \cdot h_i(c, a_{R-1}) \quad \text{for } a \geq a_R.
\end{align*}
\]

This simple formulation can be justified by the fact that unemployment benefits and pensions usually depend on past earnings, and/or non-market activities also depend on the productivity of the worker. Importantly, the replacement rate $\gamma(x)$ is allowed to depend on the state of the worker to account potential different outside options across age, gender, and/or race/ethnicity for example.

The parameter capturing the degree of statistical discrimination, $\mu$, is calibrated such that the white/black male ratio of vacancies per unemployed worker is 1.5, consistent with the findings of Bertrand and Mullainathan (2004). We find that matching that 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 V.I 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.

3.2 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 (20), (3), (13), and (18).

Given a value of $J_i(e, a + 1)$, which can be obtained by backward induction starting at the retirement age, equation (20) provides a connection between job-finding rates and the ratio $A(x) / (\kappa(x))^{1-\alpha}$. Given a series of finding rates, only partial identification is possible. It is not possible to determine, for example, if an unusually low finding rate, one that is below what is justified by the value of the match to the firm, $J$, may be due to a particularly low matching productivity or a particularly high cost of posting a vacancy.

We follow the literature in assuming that $\kappa(x)$ solely depends on the human capital of the worker so that, for example, 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 now the cost of hiring a worker only depends on the true productivity of the worker. The demographic identifier, $i$, does not play an independent role. This formulation confers a convenient scale invariance, or balanced growth, property to the model: equilibrium allocations are invariant to scaling human capitals by a non-negative factor. This can be seen from equation (20). For example, doubling all human capitals would double the value of firm with workers, $J$, but also the cost of hiring workers, $\kappa(x)$, leaving the tightness rate unchanged. Equation (20) can be used to solve for $A(x)$ as:

$$A(x) = f(x)^\alpha \left( \frac{\bar{\kappa} h(x)}{\beta J_i(e, a + 1)} \right)^{1-\alpha}. \quad (23)$$

According to this expression, matching efficiency reflects finding rates 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 finding rates, but normal cost-benefit ratios, are particularly inefficient. Any discriminatory behavior in hiring is thus, by construction, captured in the efficiency parameter $A(x)$ as an unusually low matching productivity. Similarly, markets with normal finding rates but unusually low cost-benefit ratios are also particularly inefficient. An alternative formulation would be, for example, to assume $A(x) = A$ for all $x$, while letting $\kappa(x)$ adjust to match observed finding rates according to (20). In that case, unusually low finding rates would be “explained” by unusually high hiring costs. In conclusion, our estimated matching efficiency series, $A(x)$, should be better interpreted as matching productivities relative to hiring costs.

The calibration of human capital is based on equations (13) and (18). Given a value of $W(x)$, which can be obtained by backward induction starting at the retirement age, equation (18) provides a connection between observed wages and $h(x)$, $\Theta(x)$ and/or $\bar{c}(x)$. Works by Card et. al. (2016) and Isojarvi (2019) suggests that differential bargaining powers have modest effects on explaining wage differentials. For this reason, we assume identical bargaining power for all groups, and following the literature we further assume that the Hosios condition holds so that $\phi_i(x) = \alpha = 0.5$ and $\Theta = 1$.\footnote{Cordoba et. al. (2020) show that the Hosios condition is a sufficient condition for}
Equation (18) can be written as:

\[(1 + \gamma(x)) h(x) = 2w(x) - \beta W(x).\]  

(24)

This expression is the basis for the reverse engineering of human capital stocks. Similarly 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 non-market value. This implies that a particularly low wage may be due to a particularly low human capital of the worker, but also could be due to a particularly non-market valuation of the worker's human capital which weakens the worker's position during wage negotiations.

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 \(\gamma\) such that the average consumption during unemployment in the model is about 40 percent of the average consumption for the employed, following Shimer (2003). The calibrated value of \(\gamma\) 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 the retirement. Our results are robust to different plausible values of \(\gamma_R\). Given \(\gamma(x)\) and observed series of wages, \(w(x)\), Equation (24) can be used to obtain human capital series, and Equation (1) could be used to obtain \(y_i\) and \(r(x)\) as \(y_i = h(0, 0, i, E)\) and \(r(x) = \frac{1}{\gamma} \ln h(x)\).

An implication of assuming \(\gamma(x) = \gamma\) is that any discriminatory behavior affecting wages will not be attributed at all to discrimination outside the labor market. Only discrimination during hiring and in the workplace could 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, \(r(x)\). In fact, the traditional interpretation of differences in returns to experience obtained from Blinder-Oaxaca decompositions is that they reflect some type of discrimination. The robustness section, Section 5, 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 (24) to back up 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 actually 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 C and D, along with the calibration algorithm. To further clarify the interpretation of the differences
decentralized markets to be efficient even in the presence of learning by doing and non-participation. As mentioned in Footnote 7, our allocations are not fully efficient since we assume, for tractability, that unemployment is the only outside option during bargaining.
in job-finding rates between unemployed and nonparticipant, we calibrate the search effort for nonparticipants, \( \psi_i(a) \). To do that, we need an additional restriction. We assume that the general matching efficiency is equal for both unemployed and nonparticipants, \( A_i(a, U) = A_i(a, N) = A_i(a) \), which then implies that \( \psi_i(a) \) captures unexplained differences in job-finding rates between unemployed and nonparticipants.

### 3.3 Calibration results, 1998–2018

#### 3.3.1 Human capital

Figure 4 displays average reverse-engineered human capital, average wage, average experience and average returns to experience profiles over the life cycle for eight demographic groups. As described earlier, human capital profiles are obtained such that the model exactly matches average life-cycle wages. Pre-market, or schooling, human capital, \( y_i \), is 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 and returns to experience could reflect differential occupational choices but also discrimination. 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 and human capital growth rate in the future. However, returns to experience can also capture discrimination to some extent: returns to experience are closely connected to promotions over the career, and if certain demographic groups are discriminated in promotions, that would be captured in the calibrated returns to experience.

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 is closely associated to average wages during most of the life-cycle until around age 55. In particular, human capital starts low, grows faster for young workers, and the growth slows down over the life cycle. Our series for White males is roughly consistent with the ones obtained by other search models that also find a close association between wages and human capital (Bowless and Liu, 2013, pg 306). The association is not perfect, however. First, wages grow faster than human capitals, until around age 50, reflecting improving labor market conditions over the life-cycle, such as lowering separation rates and increasing finding rates. Second, human capitals do not exhibit a clear inverted-U shape of wages. In fact, the model predicts a divergent path of wages and human capital after age 55, with wages falling while human capital still increasing. The fall in wages reflects the effect of a finite working life which gradually reduces the surplus of the match, and

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14Search effort of all unemployed groups is assumed to be equal to 1.
15See Appendix C for the dis-aggregated results for college and non-college groups. The findings described in this Section are generally robust to the disaggregation.
therefore wages, as the worker approaches retirement. This feature is consistent with similar life-cycle search models, such as Hairault et al. (2007), Cheron et al. (2013), or Menzio et al. (2016). A 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, in spite of their falling wages.\footnote{An 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 et al. (2013).}

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 displays human capital estimates for other, less studied, demographic groups. These profiles exhibit similar properties as those of White males: (i) human capital follow wages to a large extent until age 55; (ii) wages tend to grow faster than human capital early in the life cycle; and (iii) human capital and wages tend to diverge after age 55. We find significant variation in human capital profiles along all demographic dimensions: age, education, gender, and race/ethnicity. Within race/ethnicity, males have higher levels of human capital over the life cycle compared to females. But there are two sub-periods with markedly different evolution. Early in the life-cycle and up to around age 33, female human capitals grow faster than that of males (see Figure 3.d), and in the case of Hispanics, females actually have more human capital than males on average. Such convergence in human capitals across genders is not reflected in
wages partly because of the slowly weakening female labor market as job separation rates increase. Females then face stagnating 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 (Figure 4.c) but also due to a decline in the returns to experience (Figure 4.d).

Within gender, we also find fairly large differences in human capital profiles for different races/ethnicities which 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, 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 females groups, followed by White females. Again, Black and Hispanic females have fairly 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. Black males average experience is atypical of males and driven by their unusual high job separation rates and low job-finding rates. They also have unusually lower 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 start from a significantly higher level and grow rapidly until age 35 for females and age 40 for males. However, unlike for other groups, their human capital start decreasing after that. There are at least two possible explanations. First, the shape of the human capital 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 as 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 time periods: 1989–2018 and 1998–2018. Our hypothesis is that if the cohort effect is strong, the results should be different between these two time periods, as 1989–2018 periods include older cohorts. However, we do not find this to be the case which implies that there are likely to other explanations. Another possible reason could be that skilled Asians face relatively more obstacles in terms of promotions. There are some evidence on that: while Asians are the most educated group (50.6 % of 25 years or older has at least Bachelor’s degree compared to the national average 30.1 %), they are the least likely group to be promoted to managerial positions and they are not well represented in executive positions (Gee & Peck 2017, EEOC 2019). An exclusion of Asians from the highest paid positions could then show up as a stagnating wages and human capital in the data.
3.3.2 Matching efficiency

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/or 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. But while they focus on aggregate business cycle properties, our focus is on life-cycle and demographic features.

Figure 5 shows the job-finding rates for the unemployed and the reverse-engineered matching efficiencies of the unemployed. 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, for Black females. These two groups exhibit the highest and the lowest finding rates, respectively, and also end up being the ones with the highest and lowest matching efficiencies. Thus, simple cost/benefit analysis cannot fully explain these outermost finding rates without significant differences in matching efficiency. A closer look at the calibrated profiles reveal, however, a more complex relationship. In particular, various of the large systematic gaps in 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 various groups. This is particularly clear for White males and White females, as well as Hispanic females. In those cases, the falling finding rates over the life-cycle are explained largely by the declining value of the match as the end of the match approaches. A strong downward trend in matching efficiency is clear for Hispanic and Asian males, and less strong but clear for Black males. For those groups, age discrimination may play an important role. Second, in spite of their lower finding rates, matching efficiency is relatively high for Hispanic females and Asian males.

Our third observation relates to gender gaps. Similarly 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 race/ethnicity, followed by Asians, Blacks and Whites respectively. The gender gap for Whites is small and disappears at around age 40. Finally, when it comes to racial/ethnic differences in matching efficiency,

\[ A \text{ possible alternative explanation for the high finding rates of Hispanics would be that they have weaker outside options depending on legal status and language barriers. Although a weaker outside option could explain the particularly low wage rate of Hispanic, still a high matching efficiency will be required. See Section V for details. } \]
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 among Black and White males and a larger and persistent gap between Black and White females and Asian and White females. As it will become clear in the counterfactual exercises below, the reason why White males do not exhibit a particularly high matching efficiency, in spite of their observed high finding rates, is their lower separation rates and higher returns to experience. Everything else the same, 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 for nonparticipants, $\psi^N_i(a)$, over the life cycle, and the detailed results are presented in the Appendix. To summarize the results, the search effort is higher for younger workers and it decreases with age for most of the groups, consistent with the intuition that young workers are more actively attached to labor market. The search effort is also typically higher for males than females, and lowest for Whites. This last result is needed for the model to account for the fact that job-finding rates, out of non-participation, tend to be lower for Whites in spite of their lower separation rates and higher returns to experience which should have induced finding rates to be higher than normal.
4 Decomposition

In this section, we assess the quantitative role of the calibrated parametric wedges in accounting for differences in labor market outcomes as well as in their macroeconomic significance. We consider four set of counterfactuals: one that eliminates all gaps simultaneously, one that eliminates gender gaps only, one that eliminates race/ethnic gaps only, and one that eliminates educational gaps only. In each counterfactual, we close the wedges in exogenous variables, one by one, between the comparison group and the baseline, or reference, group, and calculate the effect on labor market outcomes. This decomposition informs us about the relative importance of each exogenous variable in accounting for labor market disparities. Workers can differ along 9 dimensions: human capital parameters ($y(x), r(x)$), matching efficiencies ($A(x), \psi(x)$), exogenous labor market flows ($\pi_{EN}(x), \pi_{EU}(x), \pi_{UN}(x), \pi_{NU}(x)$), and initial mass distribution among each employment status, $s$, at the beginning of their life cycle ($m_s^*(0, a)$).

Aggregate impacts are calculated as weighted averages of the dis-aggregated impacts using each group’s population share in 2018 as a weight. For more precision, we use the calibrated parameters for the skilled/unskilled categories, as reported in the Appendix, rather than the just the aggregate categories reported in Section 3.18

We also assess the quantitative importance of statistical discrimination by running a counterfactual in which $\mu$ is set to 0. This prevents firms and workers from using group-specific job destruction rates when deciding vacancy creation and when negotiating wages. They use instead job separation rates of the corresponding reference group in the counterfactual.19

In order 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 four 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 contribution of individual factors could result in figures like $+150\%, +50\%$ and $-100\%$. Values like these would suggest a relative importance of each individual factor but the exact ranking is sometimes unclear. In order to keep individual contributions bounded by 100% and adding to 100%, we define the absolute contribution as the value of the raw contribution relative to sum of the raw contributions in absolute values. In the example above, the absolute contributions are $150/300=50\%, 50/300=16.6\%$ and $-100/300=-33.3\%$. The absolute values of these contributions add to 100%. This methodology is helpful as it indicates

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18 The results are qualitative similar if only aggregate categories, as described in Section 3, are utilized. Quantitatively, the results reported in this section, based on the more dis-aggregated categories, provide a larger role for initial human capitals and a lesser role for job separation rates.

19 The exercise is different from the one carried out for the non-statistical discrimination model (NSD) described in section 5. This section uses the calibrated parameters of the SD model ($\mu = 1$) to assess what happens if $\mu$ is set to zero so that firms cannot statistically discriminate based on job separation probabilities.
that the first factor is the main determinant of the gap, while the third factor is the second most important determinant, although its contribution is negative. The proposed methodology affects how accounting results are reported for variables such as unemployment, tightness, and finding rates but has minor impact on other variables such as wages, employment or life-time earnings. For completeness, the tables also report the raw values.

4.1 Skilled White Male Premium

Our first counterfactual exercise uses Skilled White Males (WMS) of the same age as the reference group. We then equate, one by one, all the parameters of other groups to the values of the reference group, and assess their individual impact. This exercise eliminates a number of gaps simultaneously: educational gaps, gender gaps, and race/ethnicity gaps. It also provides an upper bound for the potential aggregate gains of eliminating all types of labor market disparities, frictions and/or discrimination. Figure 6 shows the decomposition results for six variables and all demographic groups. The dots in the graphs are the observed gaps. Table 2 reports corresponding decomposition results for selected labor market variables. The first row of the table shows average observed gaps while the second row shows the explained gaps calculated as the sum of the individual effects listed in the table. The unexplained part of the gap is due to interactions between individual components. The first part of the table shows the decomposition results in levels, while the second parts reports the percentage contributions to the explained gap, including the estimated contribution of statistical discrimination.

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 sets of parameters account for around three fourths of the average explained wage gaps, with differences in initial human capitals accounting for around half of the explained wage gap. Search parameters accounts for the remaining one fourth of the explained wage gap. This split is similar to other findings in the search literature. For example, Bowles and Liu (2014, pg 305) find that “human capital accumulation accounts for 50% of total earnings growth, job search accounts for 20%, and the remaining 30% is due to the interactions of the two.” Our corresponding decomposition, taking into account that the explained gap is 77% of the actual wage gap, are 57%, 20% and 23%. The similarity of the split is perhaps reassuring given that Bowls and Liu 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 NLSY79 data rather than CPS. The key role of human capital variables reflect the fact that the reference group, Skilled White Males, generally display higher educational levels and higher average returns to experience, with the exception of Asian groups, which exhibit a significantly larger initial human capital but also significantly lower average returns to experience than the reference group. In general, the explained components of the gaps is around 80% in the decompositions that
follow. For that reason, we focus our comments on the decomposition of the explained components.

The third most important wedge in accounting for the explained wage gaps is in the job destruction rate to non-participation ($\pi_{EN}$). This wedge alone accounts for around 19% of the explained wage gaps. Part of this effect comes from the fact that a high $\pi_{EN}$ is directly related to career interruptions, lower experience, and slower accumulation of human capital. But the majority comes from the fact that a high $\pi_{EN}$ weakens a worker’s outside option in the 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 and non-participation rates are largely driven by the wedges in separation rates, mainly in $\pi_{EN}$ although wedges in $\pi_{EU}$ also play a significant role. High separation rates directly leads to lower employment and higher non-participation, but it is also the major determinant of the differences in the probability of moving back to employment, as seen when looking at the decomposition for the labor market tightness and the job finding rate of the unemployed, $\theta^U$ and $\pi_{UE}$ respectively. The second most important wedge is in returns to experience, $r(x)$, particularly affecting tightness and finding rates. These returns are key for vacancy posting as they determine the expected long-term prospects of a match. Notice that while differences in initial human capitals are key for wage gaps, they play no role in explaining gaps in other labor variables such as employment, tightness or finding rates. The reason is that, as discussed in
Table 2: Decomposition Skilled White Male Premium

<table>
<thead>
<tr>
<th>Wage</th>
<th>Emplo</th>
<th>Unemp</th>
<th>Part</th>
<th>Non-Par</th>
<th>$\theta$</th>
<th>$\theta_0$</th>
<th>$\pi_E$</th>
<th>$\pi_N$</th>
<th>$\mu$</th>
<th>$\sum absolute contributions$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average gap (weighted)</td>
<td>10.34</td>
<td>11.6%</td>
<td>-0.9%</td>
<td>11.7%</td>
<td>-12.7%</td>
<td>20.2%</td>
<td>7.9%</td>
<td>4.3%</td>
<td>2.0%</td>
<td>37.74</td>
</tr>
<tr>
<td>Explained gap</td>
<td>8.01</td>
<td>14.9%</td>
<td>-0.2%</td>
<td>14.7%</td>
<td>-14.7%</td>
<td>19.3%</td>
<td>8.0%</td>
<td>4.4%</td>
<td>2.5%</td>
<td>28.12</td>
</tr>
<tr>
<td>Initial human capital ($y$)</td>
<td>3.81</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>35.5%</td>
</tr>
<tr>
<td>Matching productivity ($A$)</td>
<td>-0.05</td>
<td>-0.5%</td>
<td>-0.2%</td>
<td>-0.3%</td>
<td>0.3%</td>
<td>-0.7%</td>
<td>-1.7%</td>
<td>-0.4%</td>
<td>-0.24</td>
<td></td>
</tr>
<tr>
<td>Search-effort nonparticipants ($\psi$)</td>
<td>0.18</td>
<td>2.0%</td>
<td>0.0%</td>
<td>2.0%</td>
<td>-2.0%</td>
<td>2.5%</td>
<td>-0.7%</td>
<td>1.9%</td>
<td>1.13</td>
<td></td>
</tr>
<tr>
<td>Returns to experience ($r$)</td>
<td>2.18</td>
<td>1.2%</td>
<td>-0.2%</td>
<td>1.0%</td>
<td>-1.0%</td>
<td>9.6%</td>
<td>3.7%</td>
<td>4.5%</td>
<td>0.5%</td>
<td>29.6%</td>
</tr>
<tr>
<td>Separation rate to Unempl. ($\pi_{EU}$)</td>
<td>0.23</td>
<td>1.3%</td>
<td>-0.7%</td>
<td>0.6%</td>
<td>-0.6%</td>
<td>1.9%</td>
<td>0.6%</td>
<td>0.5%</td>
<td>0.2%</td>
<td>8.8%</td>
</tr>
<tr>
<td>Separation rate to Non-p. ($\pi_{EN}$)</td>
<td>1.52</td>
<td>10.4%</td>
<td>-0.5%</td>
<td>9.9%</td>
<td>-9.9%</td>
<td>14.8%</td>
<td>3.7%</td>
<td>4.5%</td>
<td>0.5%</td>
<td>7.38</td>
</tr>
<tr>
<td>Flow Unempl. To Non-p. ($\pi_{UN}$)</td>
<td>0.11</td>
<td>-0.2%</td>
<td>0.7%</td>
<td>0.5%</td>
<td>-0.5%</td>
<td>-3.8%</td>
<td>-1.4%</td>
<td>-1.3%</td>
<td>-0.5%</td>
<td>0.11</td>
</tr>
<tr>
<td>Flow Non-p. to Unempl. ($\pi_{NU}$)</td>
<td>0.04</td>
<td>0.4%</td>
<td>0.4%</td>
<td>0.8%</td>
<td>-0.8%</td>
<td>-0.2%</td>
<td>-0.2%</td>
<td>-0.1%</td>
<td>-0.1%</td>
<td>0.25</td>
</tr>
<tr>
<td>Initial distribution of pop. ($m_0$)</td>
<td>0.01</td>
<td>0.2%</td>
<td>0.0%</td>
<td>0.1%</td>
<td>-0.1%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>10.14</td>
</tr>
</tbody>
</table>

Section 3.3, the model is scale invariant in human capital levels. Interestingly, equating the matching efficiencies in the unemployed pool, $A(x)$, to that of the reference group would actually further increase most labor markets gaps. The reason is that the calibrated matching efficiency for Skilled White Males is more on the average level while some groups, such as Asian and Hispanics, tend to exhibit higher matching efficiency. However, the reference group enjoys a significant higher matching productivity out of the nonparticipating pool, $\psi(x)$, which explains 42% of the gap in finding rates out of the nonparticipating pool. The role of taste-based discrimination in hiring thus seems limited when considering the unemployed but maybe significant for the nonparticipants.

The key labor market outcome of the model is the average life-time earnings of workers, $W(x)$, as defined by equation (9). This average welfare measure takes into account all the wage and employment information of the worker: 20

The decomposition results for the average $W$ somewhat follows closely the decomposition results for wages, emphasizing the roles of human capital parameters and $\pi_{EN}$. However, as $W$ depend closely on both life-cycle wages and employment, the role of $\pi_{EN}$ is greater and the role of $y_i$ is smaller in generating these gaps compared to the wage gap decomposition. We find that, from

20 Since a period in the model is a quarter, $W$ is measured in quarters of earnings.
the point of view of average life-time earnings, \( W \), human capital differences accounts for 50% of total earnings disparities, job search accounts for 25%, and the remaining 25% is due to the interactions of the two.

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 job posting and wage bargaining decisions. Actual separation rates are still used when calculating job flows into unemployment and non-participation, 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, tightness rate, job finding rate, and welfare gaps. Around 70% of the role of \( \pi_{EU} \) and \( \pi_{EN} \) in generating wage gaps arises from firms’ differential treatment of groups based on their job destruction rates, while the rest is coming through the direct channel. According to the model, higher job destruction probabilities lowers a worker’s outside option in the wage negotiation, leading to lower wages. Around half of the gaps in labor market tightness and job-finding rates can be explained by the statistical discrimination, according to the model. Firms post less vacancies to workers with higher job destruction rates. Around 24 percent of the overall welfare gaps over the life cycle are coming through discrimination channel. The contribution of statistical discrimination is smaller when looking at the employment and non-participation outcomes as these outcomes depend 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 outcomes gaps between different educational groups, genders and race/ethnicity. According to Tables 2, statistical discrimination alone could explain between 12-15% of wage, employment, unemployment and non-participation gaps, and around half the gaps in labor market tightnesses, and job-finding rates. The impacts on life-cycle welfare gaps are also large, of around 24% percent.

\subsection*{4.2 Skill Gaps / Skill Premium}

Our second exercise decomposes the sources of skill gaps, or skill premium. They are gaps in labor market outcomes between skilled and unskilled individuals of the same gender, race/ethnicity and age. As shown in Table 1, gaps between the skilled and unskilled are the larger component of all gaps. They represents 46\%, 42\% and 40\% of the overall explained gaps in wages, life-time earnings and employment respectively.

The results of the decomposition are shown in Figure 7 and Table 3. The exercise uses skilled individuals of the same gender, race/ethnicity and age as the reference group. As expected, the two human capital variables, initial human capitals and returns to experience, accounts for most of the skill premium in wages and life-time earnings, 83\% and 74\% respectively, and for between 26\% to 34\% of the corresponding premiums in job finding and tightness rates. Initial human capital is the dominant factor accounting for around 60\% of the skill
wage premium and for around 50% of the premium in life-time earnings.

But an important share of skill premiums are explained by search frictions, in particular by wedges in separation rates. The lower separation rates of skilled workers account for 12.7%, 61% and 18% of the premiums in wages, employment, and life-time earnings respectively. Statistical discrimination accounts, according to the model, for 9.3%, 13.5% and 15.2% of skill premiums in wages, employment, and life-time earnings, and between 22% to 47% of the skill premiums in job finding and tightness rates.

These accounting results indicate that higher human capitals, the ability of the 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 search frictions and statistical discrimination that favors skilled workers.

4.3 Gender Gaps / Male Premium

Gender gaps are the second larger of all gaps. According to Table 1, they account for 29%, 31% and 51% of the overall explained gaps in wages, life-time earnings and employment respectively. The decomposition results, shown in Figure 8 and Table 4, suggests similar roles for human capital and search frictions in explaining gender gaps in wage and life-time earnings, of 54% and 46% respectively, but a minimum role for human capital variables in explaining the significant gender gaps in employment, job finding, and tightness rates.
### Table 3: Decomposition - Skill Gap

<table>
<thead>
<tr>
<th></th>
<th>Wage</th>
<th>Empl</th>
<th>Unemp</th>
<th>Part</th>
<th>Non-Par</th>
<th>$\theta^0$</th>
<th>$\theta^0$</th>
<th>$\mu_{UE}$</th>
<th>$\mu_{NE}$</th>
<th>$W$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average gap (weighted)</td>
<td>4.73</td>
<td>5.6%</td>
<td>-0.5%</td>
<td>5.0%</td>
<td>-5.0%</td>
<td>7.4%</td>
<td>4.7%</td>
<td>5.0%</td>
<td>-5.0%</td>
<td>15.75</td>
</tr>
<tr>
<td>Explained gap</td>
<td>3.92</td>
<td>5.7%</td>
<td>-0.3%</td>
<td>5.3%</td>
<td>-5.3%</td>
<td>7.4%</td>
<td>4.1%</td>
<td>0.8%</td>
<td>1.5%</td>
<td>12.58</td>
</tr>
<tr>
<td>Initial human capital ($y$)</td>
<td>2.45</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>6.51</td>
</tr>
<tr>
<td>Matching productivity ($A$)</td>
<td>-0.09</td>
<td>-0.7%</td>
<td>0.2%</td>
<td>0.6%</td>
<td>-0.6%</td>
<td>-0.9%</td>
<td>-0.3%</td>
<td>-1.9%</td>
<td>-0.6%</td>
<td>-0.37</td>
</tr>
<tr>
<td>Search-effort nonparticipants ($\nu$)</td>
<td>0.07</td>
<td>1.3%</td>
<td>0.0%</td>
<td>1.3%</td>
<td>-1.3%</td>
<td>-1.1%</td>
<td>1.7%</td>
<td>-0.4%</td>
<td>1.4%</td>
<td>0.62</td>
</tr>
<tr>
<td>Returns to experience ($r$)</td>
<td>0.96</td>
<td>0.6%</td>
<td>-0.1%</td>
<td>0.5%</td>
<td>-0.5%</td>
<td>4.7%</td>
<td>1.3%</td>
<td>1.6%</td>
<td>0.4%</td>
<td>3.44</td>
</tr>
<tr>
<td>Separation rate to Unempl. ($\pi_{EU}$)</td>
<td>0.16</td>
<td>1.0%</td>
<td>-0.5%</td>
<td>0.5%</td>
<td>-0.5%</td>
<td>1.4%</td>
<td>0.4%</td>
<td>0.4%</td>
<td>0.1%</td>
<td>0.57</td>
</tr>
<tr>
<td>Separation rate to Non-p. ($\pi_{EN}$)</td>
<td>0.34</td>
<td>3.4%</td>
<td>-0.2%</td>
<td>3.2%</td>
<td>-3.2%</td>
<td>4.4%</td>
<td>1.2%</td>
<td>1.5%</td>
<td>0.3%</td>
<td>1.76</td>
</tr>
<tr>
<td>Flow Unempl. To Non-p. ($\pi_{UN}$)</td>
<td>0.03</td>
<td>0.0%</td>
<td>0.2%</td>
<td>0.2%</td>
<td>-0.2%</td>
<td>-0.9%</td>
<td>-0.3%</td>
<td>-0.3%</td>
<td>-0.1%</td>
<td>0.03</td>
</tr>
<tr>
<td>Initial distribution of pop. ($m_0$)</td>
<td>0.00</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.02</td>
</tr>
</tbody>
</table>

|                                | $\mu$ | 0.38 | 0.01 | 0.00 | 0.01   | 0.06       | 0.02       | 0.02       | 0.01       | 2.02 |

|                                | 59.9%| 0.0% | 0.0%  | 0.0% | 0.0%    | 0.0%       | 0.0%       | 0.0%       | 0.0%       | 48.9% |
|                                | 23.3%| 8.5% | 8.5%  | 7.7% | -7.7%   | 34.8%      | 24.4%      | 25.9%      | 13.8%      | 25.1% |
|                                | -2.1%| -10.2%| 13.5% | 8.9% | -8.9%   | -6.6%      | -5.9%      | -30.2%     | -21.0%     | -2.8% |
|                                | 1.7% | 17.6%| -0.3% | 19.7%| -19.7%  | -8.0%      | 32.7%      | -6.0%      | 32.7%      | 4.9% |
|                                | 3.9% | 13.5%| -40.4%| 7.3% | -7.3%   | 10.4%      | 7.5%       | 7.0%       | 3.5%       | 4.3% |
| To unemployment ($\pi_{EU}$)   | 8.2% | 47.2%| -13.9%| 49.8%| -49.8%  | 32.1%      | 23.2%      | 23.8%      | 10.5%      | 13.2% |
| To non-participation ($\pi_{EN}$) | 0.6% | 0.4% | 14.1% | 2.3% | -2.3%   | -6.5%      | -5.6%      | -4.8%      | -3.4%      | 0.2% |
| $\pi_{EN}$                     | 0.1% | 1.5% | 8.8%  | 3.3% | -3.3%   | -1.5%      | 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%       | 0.1%       | 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% |

|                                | Total Contribution | 9.3% | 13.5%| -11.0%| 12.9%  | -12.9%     | 46.9%      | 38.4%      | 34.4%      | 22.6% |
|                                | As share of $d$    | 76.7%| 22.2%| 20.3% | 22.7%  | 22.7%      | 110.3%     | 125.2%     | 111.5%     | 161.2% |

Ration rates to non-participation ($\pi_{EN}$) are either the major or a major factor explaining gender gaps, and most this role enters through statistical discrimination. The respective contributions of $\pi_{EN}$ and statistical discrimination are: for wages, 29% and 16%; for employment, 59% and 10%; for life-time earnings, 36% and 25%; for finding rates of the unemployed 36% and 32%; for the tightness rate of the unemployed, 49% and 44%; and for the tightness rate of the nonparticipants, 32% and 38%.

Hsieh et. al. (2019) wonders why Justice O’Connor, like many women in the 1950’s, had difficulties finding a job early in her career, despite being ranked third in her class at Stanford Law School. Justice Ginsburg faced similar difficulties. A simple model of career choice, like the Roy model used by Hsieh et. al., would have problems rationalizing high unemployment rates of high-skilled willing-to-work women, just like the justices. Our search model with statistical discrimination can rationalize these situations. According to the model, if separation rates are high among skilled women, which was the case in the 1950’s, then all sort of labor market outcomes are affected for skilled women, particularly job-finding and unemployment rates.
4.4 Race-Ethnic Gaps / White Premium

Race/ethnic gaps are the third largest of all gaps. According to Table 1, they account for around 11-13% of the overall gaps in wages, life-time earnings and employment respectively. The decomposition results, shown in Figure 9 and Table 5, suggest a strong role for human capital, particularly for returns to experience, and separation rates in explaining race/ethnic gaps. Human capital explains 61% and 48% of the wage and life-time earnings gaps, and 17% and 22% of the racial gaps in job finding and tightness rate of the unemployed.

Separation rates and statistical discrimination explain, respectively, 30.5% and 22.7% of the racial wage gap, 35% and 30.8% of the life-time earnings racial gap, 60% and 14% of the employment racial gap, 49% and 54% of the racial gap in the tightness rate of the unemployed, and 38% and 41% of the gap in findings rate of the unemployed.

These aggregate results hide some important differences among race/ethnic groups. As shown in Figure 9, lower matching efficiency is an important contributor of 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. On the other hand, Hispanic groups, with the exception of skilled Hispanic females, and unskilled Asian females, exhibit particularly high matching efficiencies. These results suggest reverse prejudice as employers may actually prefer certain minority groups.
Table 4: Decomposition Gender Gaps

<table>
<thead>
<tr>
<th>Wage</th>
<th>Empl</th>
<th>Unemp</th>
<th>Part</th>
<th>Non-Par</th>
<th>( \theta'^m )</th>
<th>( \theta'^n )</th>
<th>( \gamma_k )</th>
<th>( \gamma_h )</th>
<th>( \gamma_w )</th>
<th>( \alpha )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average gap (weighted)</td>
<td>3.03</td>
<td>6.9%</td>
<td>0.4%</td>
<td>7.3%</td>
<td>-7.3%</td>
<td>5.2%</td>
<td>2.8%</td>
<td>3.3%</td>
<td>1.7%</td>
<td>11.5%</td>
</tr>
<tr>
<td>Explained gap</td>
<td>2.84</td>
<td>8.0%</td>
<td>0.7%</td>
<td>8.7%</td>
<td>-8.7%</td>
<td>5.9%</td>
<td>3.4%</td>
<td>3.4%</td>
<td>2.1%</td>
<td>10.62</td>
</tr>
<tr>
<td>Initial human capital (y)</td>
<td>1.17</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>3.14</td>
</tr>
<tr>
<td>Matching productivity (A)</td>
<td>0.14</td>
<td>1.0%</td>
<td>0.1%</td>
<td>0.9%</td>
<td>-0.9%</td>
<td>1.0%</td>
<td>0.3%</td>
<td>2.0%</td>
<td>0.6%</td>
<td>0.48</td>
</tr>
<tr>
<td>Search effort nonparticipants (v)</td>
<td>0.16</td>
<td>1.4%</td>
<td>0.0%</td>
<td>1.4%</td>
<td>-1.4%</td>
<td>-1.8%</td>
<td>1.9%</td>
<td>-0.5%</td>
<td>1.5%</td>
<td>0.87</td>
</tr>
<tr>
<td>Returns to experience (r)</td>
<td>0.47</td>
<td>3.0%</td>
<td>0.0%</td>
<td>2.0%</td>
<td>-0.2%</td>
<td>0.0%</td>
<td>0.6%</td>
<td>0.6%</td>
<td>0.2%</td>
<td>2.07</td>
</tr>
<tr>
<td>Separation rate to Unempl. (( \gamma_{Eu} ))</td>
<td>-0.10</td>
<td>-0.6%</td>
<td>0.2%</td>
<td>-0.4%</td>
<td>0.4%</td>
<td>-0.7%</td>
<td>-0.3%</td>
<td>-0.3%</td>
<td>-0.1%</td>
<td>-0.37</td>
</tr>
<tr>
<td>Separation rate to Non-p. (( \gamma_{En} ))</td>
<td>0.89</td>
<td>5.6%</td>
<td>-0.2%</td>
<td>5.4%</td>
<td>-5.4%</td>
<td>8.3%</td>
<td>2.1%</td>
<td>2.5%</td>
<td>0.4%</td>
<td>4.12</td>
</tr>
<tr>
<td>Flow Unempl. To Non-p. (( \gamma_{UN} ))</td>
<td>0.07</td>
<td>-0.1%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.03</td>
</tr>
<tr>
<td>Flow Non-p. to Unempl. (( \gamma_{UN} ))</td>
<td>0.04</td>
<td>0.4%</td>
<td>0.5%</td>
<td>0.9%</td>
<td>-0.9%</td>
<td>1.0%</td>
<td>0.3%</td>
<td>2.0%</td>
<td>0.6%</td>
<td>4.38</td>
</tr>
<tr>
<td>Initial distribution of pop. (( \mu ))</td>
<td>0.01</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>2.87</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Absolute Contributions</th>
<th>(Absolute values add to 100%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wage</td>
<td>Empl</td>
</tr>
<tr>
<td>Initial human capital (y)</td>
<td>38.4%</td>
</tr>
<tr>
<td>Returns to experience (r)</td>
<td>15.3%</td>
</tr>
<tr>
<td>Matching productivity (A)</td>
<td>4.7%</td>
</tr>
<tr>
<td>Search-effort nonparticipants (v)</td>
<td>5.2%</td>
</tr>
<tr>
<td>To unemployment (( \gamma_{Eu} ))</td>
<td>-3.3%</td>
</tr>
<tr>
<td>To nonparticipation (( \gamma_{En} ))</td>
<td>29.4%</td>
</tr>
<tr>
<td>Others</td>
<td>2.3%</td>
</tr>
<tr>
<td>Statistical discrimination</td>
<td>16.0%</td>
</tr>
<tr>
<td>As share of ( d )</td>
<td>61.4%</td>
</tr>
</tbody>
</table>

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. Everything else the same, Whites received around 50% more callbacks for interviews in their field experiment. What is the source of this difference? Our exercise sheds some light. According to our model, there are three sets of 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, in particular in returns to experience, and statistical discrimination explains most of the gap. Prejudice in hiring is of secondary importance on average, but potentially important for certain groups. For example, our disaggregated results show that prejudice could explain up to 10% of lower job-finding rate of unskilled Black males relative to unskilled White males.
5 Robustness checks

This section provides further support to the use of 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 non-market compensations, to vary across demographic groups enough as to explain wage gaps. We find that these alternative formulations are problematic. We performed further robustness checks not reported. We find that our main results are robust to the following alternatives. (i) different period of analysis; (ii) full time versus part time.

5.1 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 $\mu$ is set to be 0. This calibration strategy implies that firms are not able to statistically discriminate workers based on group-specific job separation probabilities, $\pi_{EN}$ and $\pi_{EU}$. Instead, the calibration assumes that firms and workers only observe a common set of job separation rates, affected only by education, age and experience, but not by demographic indicators. For convenience, we choose job separation rates of White males as the common rates just because White males is the reference group utilized in other parts of the paper, say when comparing wage gaps. The

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure9.png}
\caption{Decomposition Race Gaps}
\end{figure}
results in this section are robust to selecting other natural reference groups, such as population averages by age, experience and education.\textsuperscript{21} Figure 10 shows human capitals and matching productivities of the NSD model relative to the SD model for various demographic groups over the life-cycle. A salient feature of these graphs is that the NSD model requires significantly lower human capitals, relative to White males, and lower matching efficiencies than the SD model. The percentage required drop in matching efficiency is larger and more persistent over the life-cycle than the required drop in human capitals. The large drop in matching efficiencies of all groups relative to White males suggests that reducing the role for statistical discrimination, by setting $\mu = 0$, increases the potential for taste based discrimination (TBD). In particular, regarding gender and race discrimination, the SD model suggests a relatively small potential role for TBD since matching efficiencies are only slightly lower for White females and Black males relative to White males. But the NSD model requires significantly lower matching efficiencies for these two groups, suggesting a larger potential role for TBD.

The direct effect of eliminating SD is to increase the value of matches with

\textsuperscript{21}Using average probabilities would be more transparent exercise because it would be a mean preserving change in destruction rates.

<p>| Table 5: Decomposition Race/Ethnic Gaps |
|-----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|</p>
<table>
<thead>
<tr>
<th>Contribution</th>
<th>Wage</th>
<th>Empl</th>
<th>Unemp</th>
<th>Part</th>
<th>Non-Par</th>
<th>$\theta$</th>
<th>$\theta^*$</th>
<th>$\pi_{u0}$</th>
<th>$\pi_{u0}$</th>
<th>$\pi_{u0}$</th>
<th>$W$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average gap (weighted)</td>
<td>1.32</td>
<td>1.8%</td>
<td>-0.6%</td>
<td>1.2%</td>
<td>-1.3%</td>
<td>7.6%</td>
<td>-0.4%</td>
<td>1.8%</td>
<td>-1.3%</td>
<td>4.34</td>
<td></td>
</tr>
<tr>
<td>Explained gap</td>
<td>1.23</td>
<td>1.6%</td>
<td>-0.5%</td>
<td>1.1%</td>
<td>-1.1%</td>
<td>6.6%</td>
<td>-0.2%</td>
<td>1.7%</td>
<td>-1.2%</td>
<td>4.04</td>
<td></td>
</tr>
<tr>
<td>Initial human capital ($y$)</td>
<td>0.35</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.96</td>
<td></td>
</tr>
<tr>
<td>Matching productivity ($A$)</td>
<td>-0.10</td>
<td>-1.5%</td>
<td>0.0%</td>
<td>-1.5%</td>
<td>1.5%</td>
<td>1.4%</td>
<td>-2.0%</td>
<td>0.5%</td>
<td>-1.6%</td>
<td>0.81</td>
<td></td>
</tr>
<tr>
<td>Search-effort nonparticipants ($\varphi$)</td>
<td>0.12</td>
<td>0.7%</td>
<td>-0.4%</td>
<td>0.3%</td>
<td>-0.3%</td>
<td>0.9%</td>
<td>0.3%</td>
<td>0.3%</td>
<td>0.1%</td>
<td>0.49</td>
<td></td>
</tr>
<tr>
<td>Separation rate to Unempl. ($\pi_{EU}$)</td>
<td>0.31</td>
<td>2.4%</td>
<td>-0.1%</td>
<td>2.3%</td>
<td>-2.3%</td>
<td>2.9%</td>
<td>0.9%</td>
<td>1.0%</td>
<td>0.2%</td>
<td>1.54</td>
<td></td>
</tr>
<tr>
<td>Flow Unempl. To Non-p. ($\pi_{UN}$)</td>
<td>0.02</td>
<td>0.0%</td>
<td>0.1%</td>
<td>0.1%</td>
<td>-0.1%</td>
<td>-0.4%</td>
<td>-0.2%</td>
<td>-0.2%</td>
<td>-0.1%</td>
<td>0.03</td>
<td></td>
</tr>
<tr>
<td>Initial distribution of pop. ($m_0$)</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.02</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Contributions</th>
<th>Worker</th>
<th>Employer</th>
<th>Unemployed</th>
<th>Part</th>
<th>Non-Par</th>
<th>$\theta$</th>
<th>$\theta^*$</th>
<th>$\pi_{u0}$</th>
<th>$\pi_{u0}$</th>
<th>$\pi_{u0}$</th>
<th>$W$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average gap (weighted)</td>
<td>24.5%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>16.7%</td>
</tr>
<tr>
<td>Returns to experience ($r$)</td>
<td>36.1%</td>
<td>4.5%</td>
<td>4.8%</td>
<td>3.7%</td>
<td>3.7%</td>
<td>22.1%</td>
<td>-14.7%</td>
<td>17.4%</td>
<td>-8.9%</td>
<td>31.0%</td>
<td></td>
</tr>
<tr>
<td>Matching efficiency</td>
<td>0.3%</td>
<td>-2.9%</td>
<td>-7.1%</td>
<td>-1.7%</td>
<td>-1.7%</td>
<td>-2.3%</td>
<td>-3.2%</td>
<td>-21.5%</td>
<td>0.5%</td>
<td>1.4%</td>
<td></td>
</tr>
<tr>
<td>Search-effort nonparticipants ($\varphi$)</td>
<td>-6.7%</td>
<td>-29.2%</td>
<td>-2.9%</td>
<td>-30.7%</td>
<td>-30.7%</td>
<td>17.4%</td>
<td>46.7%</td>
<td>13.5%</td>
<td>73.8%</td>
<td>-14.0%</td>
<td></td>
</tr>
<tr>
<td>To unemployment ($\pi_{EU}$)</td>
<td>8.5%</td>
<td>13.4%</td>
<td>36.9%</td>
<td>6.7%</td>
<td>6.7%</td>
<td>11.7%</td>
<td>-7.8%</td>
<td>9.4%</td>
<td>-4.9%</td>
<td>8.5%</td>
<td></td>
</tr>
<tr>
<td>To nonparticipation ($\pi_{EN}$)</td>
<td>22.0%</td>
<td>47.0%</td>
<td>13.8%</td>
<td>47.5%</td>
<td>47.5%</td>
<td>37.4%</td>
<td>-21.4%</td>
<td>28.8%</td>
<td>-7.9%</td>
<td>26.7%</td>
<td></td>
</tr>
<tr>
<td>$\mu$</td>
<td>0.33</td>
<td>0.01</td>
<td>0.00</td>
<td>0.01</td>
<td>-0.01</td>
<td>0.04</td>
<td>0.02</td>
<td>0.01</td>
<td>0.01</td>
<td>1.78</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Human Capital</th>
<th>Wage</th>
<th>Empl</th>
<th>Unemp</th>
<th>Part</th>
<th>Non-Par</th>
<th>$\theta$</th>
<th>$\theta^*$</th>
<th>$\pi_{u0}$</th>
<th>$\pi_{u0}$</th>
<th>$\pi_{u0}$</th>
<th>$W$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial human capital ($y$)</td>
<td>24.5%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
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<tr>
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<td>4.8%</td>
<td>3.7%</td>
<td>3.7%</td>
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<td>-3.2%</td>
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<td>-30.7%</td>
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<td>36.9%</td>
<td>6.7%</td>
<td>6.7%</td>
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<td>47.5%</td>
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<th>$\theta^*$</th>
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<th>$\pi_{u0}$</th>
<th>$\pi_{u0}$</th>
<th>$W$</th>
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<td>Average gap (weighted)</td>
<td>22.7%</td>
<td>13.8%</td>
<td>11.8%</td>
<td>12.7%</td>
<td>12.7%</td>
<td>53.9%</td>
<td>-38.8%</td>
<td>41.3%</td>
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<tr>
<td>As share of $d$</td>
<td>74.0%</td>
<td>22.9%</td>
<td>23.2%</td>
<td>23.4%</td>
<td>23.4%</td>
<td>109.8%</td>
<td>132.7%</td>
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higher break probabilities than White males, such as women or Black males, increasing job posting and improving finding rates for those groups. To counteract this effect and thus match the observed 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 White male rates. To offset this effect, and thus match observed wages, the NSD model requires lower human capital stocks for those groups. Lower human capitals partly reduce match surpluses and discourage job posting, but the direct effect of lower separation rates dominates making 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 finding rates. In other words, a model 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 highlights the importance of utilizing a general equilibrium model rather a partial equilibrium one.

Finally, Figure 10 shows the labor market tightnesses rates for different groups relative to White males rates for the SD and NSD models. Tightnesses 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 to Black males is 1.12 is the NSD model. This small gaps is problematic for the NSD model since the evidence suggests a larger gap in the number of
The benchmark model calibrated human capital stocks using equation (24) by assuming a common replacement rate, $\gamma(x)$, for all groups. We now report results for an alternative calibration that assumes a common human capital function, and uses (24) to backup groups specific series of $\gamma(x)$. The non-market value of human capital is then given by $\gamma(x)h(x)$, a value that would allow the model to match 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 skill level.

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

6 Relation to the literature

Our model related to the literature of life-cycle search models with human capital such as Hairault et al. (2007), Cheron et al. (2013), Menzio et al. (2016) and Bowhus and Liu (2014). Barnichon and Figura (2015) and Hall and Schullhofer-Wohl (2018) also study matching efficiency under heterogeneity and segmented markets. But while they focus on aggregate business cycle properties, our focus is on life-cycle and demographic features.

Our paper relates to the large and active literature on labor market disparities between gender and race, and more specifically on 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. Literature on discrimination using dynamic, structural approaches are fairly limited. The closest paper to ours is by Gayle and Golan (2012), who
study gender discrimination and a gender wage gap by building a dynamic general equilibrium model. They find that differences in labor market experience are the most important channel to explain 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 market with frictions to be able to study simultaneously not on 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 2018, Lundborg, Plug, and 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 impacts on 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 use the general equilibrium model to assess how big fraction of the negative impacts of the nonworking periods are arising from the discriminatory behavior of the firms. Our theory relates to literature on search models with human capital growth. The literature usually study the role of human capital investment (either general or firm-specific) versus on-the-job search on the wage growth. Flinn et. al. (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 can wage growth of the workers be explained by investment in human capital versus searching for new, more productive employment opportunities. They link their results with Mincer equation and find decreasing returns to investment in both types of human capital. Burdett et. al. (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 Mincer equation to see if their model generates reasonable connection with Mincer literature. However, they assume constant returns to experience, which differs with typical decreasing returns in experience in Mincer equations. Bagger et. al. (2014) build a model along the same lines as Burdett et. al. (2014), but allow for an employee and an employer heterogeneity and productivity shocks, and they estimate the lifecycle 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 non-participation 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 through 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 et al. 2014, Elsby et al. 2015, Kroft et al. 2016, Menzio, Telyukova, and 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, and Langot 2013, Esteban-Pretel and Fujimoto 2014, Fujimoto 2013, Hairault, Cheron, and Langot 2007, Bowles and Liu 2014, Menzio, Telyukova, and 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 Vallarides-Esteban 2018 study the wage and employment gaps among Blacks and White males in a model with endogenous human capital and exogenous separation rates. They find a similar 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.

7 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 in wages or unemployment rates, between demographic groups. This paper seeks to understand the sources of unequal labor market outcomes through the lenses of the canonical labor market model: the Diamond-Mortensen-Pissarides (DMP) model. We introduce 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.

In the spirit of Chari et al. (2007), we reverse-engineered the wedges needed for the model to be able to exactly match observed series of wages and 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 rates of unemployment among demographic groups. The DMP model is the canonical model of unemployment and therefore the natural candidate for our accounting exercise. Second, the DMP provides a unified explanation for labor market variables, such as wages, employment, unemployment, and labor market participation, all of which vary systematically among demographic groups.

We find that wedges in three set of parameters are responsible for most of the labor market disparities: gaps in initial human capital ($y$), in return to experience ($r$), and in the separation rate to non-participation ($\pi_{EN}$). 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, $r$ and $\pi_{EN}$, can explain the majority of gaps in job-finding rates. We also find that a major fraction of the impact through match break probability, $\pi_{EN}$, comes through discrimination channel, emphasizing the role of statistical discrimination in labor market gaps. Wedges in matching efficiencies turned out to be quantitatively secondary. While we found quite 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 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% more callbacks for interviews in their field experiment. What is the source of this difference? Our exercise sheds some light. According to our model, there are three set of 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, in particular in returns to experience, and statistical discrimination explains most of the gap. Prejudice in hiring is of secondary importance.

Our results about the importance of statistical discrimination are consistent with a large body of empirical literature (see for example Agan & Starr 2017, Altonji & Pierret 2001, Ayres and Siegelman 1995, Bohren, Haggag, Imas, & Pope 2019, List 2004, and Zussman 2013) that find evidence on discrimination in various markets, which 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 firm to incur in a fix 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 change of a successful hire. Workers with higher returns to experience and lower separation rates produce a higher expected surplus, which induce more job posting, higher 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 hazard rates. This step would require to enrich the model considerably, or to focus on a more narrow set of demographic groups, as is standard in the literature.

References


A Proof of proposition 1

Using the definitions of surpluses given in (17), equations (3), (4) and (10) can be written as,

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

$$k(x) = \beta A(x) \theta(x)^{-\alpha} \Theta (x) S_{EU}(e, a + 1), \quad \text{(26)}$$

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

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

$$U(x) = c_i^U (e, a) + \beta \left[ U_i(e, a + 1) + f_i^U(e, a) S_{EU}(e, a + 1) + \pi_{UN}(x) S_{NU}(e, a + 1) \right]$$

$$= c_i^U (e, a) + \beta \left[ U(x') - \Delta U(x') + f_i^U(e, a) S_{EU}(e, a + 1) + \pi_{UN}(x) S_{NU}(e, a + 1) \right];$$

Subtracting the second equation from the first one:

$$S_{EU}(x) = w(x) - c_i^U (e, a) + \beta \left[ (1 - \pi_{EU}(x)) S_{EU}(x') + \Delta U(x') - f_i^U(e, a) S_{EU}(e, a + 1) \right]$$

or

$$S_{EU}(x) = w(x) - c_i^U (e, a) + \beta E \left[ S_{EU}(e, a + 1) \right]; \quad \text{(28)}$$
where \( E \left[ \bar{S}_{EU} (e, a + 1) \right] \) is the expected surplus at age \( a + 1 \) of an employed worker in state \((e, a + 1)\). It is defined as:

\[
E \left[ \bar{S}_{EU} (e, a + 1) \right] = \left[ (1 - \pi_{EU}(x)) S_{EU} (x') - \pi_{EN}(x) S_{EN} (x') - \bar{\pi}_{NU}(x) S_{NU}^i (e, a + 1) \right] - f^U_i (e, a) S_{EU}^i (e, a + 1) + \Delta U (x')
\]

Similarly, rewrite (8) as:

\[
S_{EN} (x) = c_i^N (e, a) + \beta \left[ N_i(e, a + 1) + f^N_i (e, a) S^i_{EN} (e, a + 1) + \bar{\pi}_{NU}(x) S_{NU}^i (e, a + 1) \right]
\]

\[
= c_i^N (e, a) + \beta \left[ N(x') - \Delta N(x') + f^N_i (e, a) S^i_{EN} (e, a + 1) - \bar{\pi}_{NU}(x) S_{NU}^i (e, a + 1) \right].
\]

Subtracting this equation from (27):

\[
S_{EN} (x) = w(x) - c_i^N (e, a) + \beta \left[ S_{EN} (x') + \Delta N (x') - f^N_i (e, a) S^i_{EN} (e, a + 1) \right]
\]

\[
= \beta \left[ S_{EN}^i (e, a + 1) + \Delta N (x') - f^N_i (e, a) S^i_{EN} (e, a + 1) \right] = \beta \left[ \bar{S}_{EU}^i (e, a + 1) \right].
\]

Equation (29) can be used to directly solve for \( S_{EN} \) as a function of \( J_i (e, a + 1) \). To solve for \( w(x) \), use (25) and (29) to obtain:

\[
\Theta(x) \left[ w(x) - c_i^N (e, a) + \beta E \left[ \bar{S}_{EU}^i (e, a + 1) \right] \right]
\]

\[
= h(x) - w(x) + \beta \left[ (1 - \pi_{EU}(x) - \pi_{EN}(x)) \Theta(x) S_{EU}(x') \right].
\]

Solving for \( w(x) \) gives

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

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

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

\[
= (1 - \pi_{EU}(x) - \pi_{EN}(x)) S_{EU}(x') - (1 - \pi_{EU}(x)) S_{EU}(x') + \pi_{EN}(x) S_{EN}(x') + \bar{\pi}_{NU}(x) S_{NU}(e, a + 1) + f^U_i (e, a) S_{EU}(e, a + 1) - \Delta U (x')
\]
or
\[
\Omega(x) = \pi_{EN}(x)[S_{EN}(x') - S_{EU}(x')] + \pi_{UN}(x)S'_{NU}(e, a + 1) \\
+ f_i^U(e, a)S'_{EU}(e, a + 1) - \Delta U(x').
\]

B Identification and calibration strategy

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

\[
w_i(a) = \frac{\sum_e m_i^E(e, a) w_i(e, a)}{\sum_e m_i^E(e, a_R)} \quad (30)
\]

\[
h_i(a) = \frac{\sum_e m_i^E(e, a) h_i(e, a)}{\sum_e m_i^E(e, a_R)} \quad (31)
\]

\[
c_i(a) = \frac{\sum_e m_i^E(e, a) \bar{c}_i(e, a)}{\sum_e m_i^E(e, a_R)} \quad (32)
\]

\[
f(U_i, a) = \frac{\sum_e m_i^U(e, a) f(e, a, U_i, i)}{\sum_e m_i^U(e, a_R)} \quad ; (33)
\]

\[
f(N_i, a) = \frac{\sum_e m_i^N(e, a) f(e, a, N_i, i)}{\sum_e m_i^N(e, a_R)}. \quad (34)
\]

B.1 Calibration for \(a = a_R - 1\)

We are now ready to describe the benchmark calibration of human capital parameters and matching productivities. The reverse engineering start backwards, from \(a_R - 1\). According to (30), (13), (31) and (32) the average wage at age \(a_R - 1\) satisfies

\[
w_i(a_R - 1) = \frac{\sum_e m_i^E(e, a_R - 1) w_i(e, a_R - 1)}{\sum_e m_i^E(e, a_R - 1)} \\
= \frac{\sum_e m_i^E(e, a_R - 1) [h_i(e, a_R - 1) + \Theta_i(a)] [c_i(e, a_R - 1) - \beta \Delta R_i(e, a_R)]}{1 + \Theta_i(a)} \\
= \frac{h_i(a_R - 1) + \Theta_i(a) [c_i(a_R - 1) - \beta \Delta R_i(a_R)]}{1 + \Theta_i(a)}
\]
where
\[ \Delta R_{i}(a_R) = \sum_{e} \frac{m^{E}_{i}(e, a) \Delta R_{i}(e + 1, a_R)}{m^{E}_{i}(e, a_R)} \]  
(35)

Given data for \( w_{i}(a_{R} - 1) \), this expression could be used to solve for \( h_{i}(a_{R} - 1) \) as:
\[ h_{i}(a_{R} - 1) = w_{i}(a_{R} - 1) (1 + \Theta_{i} (a)) - \Theta_{i}(a) (\epsilon_{i}^{U}(a_{R} - 1) - \beta \Delta R_{i}(a_{R})) \]  
(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 \( r_{i}(a_{R} - 1) \):
\[ h_{i}(a_{R} - 1) = y_{i} \sum_{e} \frac{m^{E}_{i}(e, a_{R} - 1) \exp(r_{i}(a_{R} - 1)e)}{m^{E}_{i}(e, a_{R} - 1)} \]  
(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 (13) as:
\[ w_{i}(e, a_{R} - 1) = \frac{1}{1 + \Theta_{i} (a)} [h_{i}(e, a_{R} - 1) + \Theta_{i}(a) (\epsilon_{i}^{U}(e, a_{R} - 1) - \beta \Delta R_{i}(e + 1a_{R}))]. \]

These wages can then be plugged into (3), (6), and (7) to find \( J_{i}(e, a_{R} - 1), \ E_{i}(e, a_{R} - 1), \ U_{i}(e, a_{R} - 1), \ N_{i}(e, a_{R} - 1) \) as well as the surpluses defined by (17) for \( a = a_{R} - 1 \).

**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 (23), (33) and (34). In particular,
\[ f(a, U, i) = A_{i}(a) \beta \frac{\sum_{e} m^{U}_{i}(e, a) (\beta J_{i}(e, a + 1)/\kappa_{i}(e, a))^{1-\alpha}}{\sum_{e} m^{U}_{i}(e, a)} \]
or solving for \( A_{i}(a) \):
\[ A_{i}(a, U) = A_{i}(a) = \left[ \frac{f(a, \bar{U}, i) \sum_{e} m^{U}_{i}(e, a)}{\sum_{e} m^{U}_{i}(e, a) (\beta J_{i}(e, a + 1)/\kappa_{i}(e, a))^{1-\alpha}} \right]^{\alpha} \]
Similarly,
\[ A_{i}(a, N) = \psi_{i}(a) A_{i}(a) = \left[ \frac{f(a, \bar{N}, i) \sum_{e} m^{N}_{i}(e, a)}{\sum_{e} m^{N}_{i}(e, a) (\beta J_{i}(e, a + 1)/\kappa_{i}(e, a))^{1-\alpha}} \right]^{\alpha} . \]

These two expressions provide the calibrated values of \( A_{i}(a) \) and \( \psi_{i}(a) \) given data on average values of finding rates for the unemployed and the nonparticipants. These formulas are valid for all ages. Given these parametric values then
job-finding rates for all \( e \), not just on average, \( f(e, a, U, i) \) and \( f(e, a, N, i) \) using (20). One can then use these job-finding rates as well as the surpluses already obtained for \( a + 1 \) to calculate \( W(x) \) as defined by (21). Next, define \( W_i^E(a) \) as:

\[
\Omega_i^E(a) = \frac{\sum_e m_i^E(e, a) \Omega(e, a, E, i)}{\sum_e m_i^E(e, a)}.
\]

According to (18), average wages satisfy:

\[
w_i(a) = \frac{1}{1 + \Theta_i(a)} \sum_e m_i^E(e, a) \left[ \Theta_i(a) \left( c_i^U + \beta \Omega_i^E(a) \right) \right] = \frac{1}{1 + \Theta_i(a)} \left[ h_i(a) + \Theta_i(a) \left( c_i^U + \beta \Omega_i^E(a) \right) \right]
\]

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

\[
h_i(a) = w_i(a) \left( 1 + \Theta_i(a) \right) - \Theta_i(a) \left( c_i^U + \beta \Omega_i^E(a) \right).
\]  

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

\[
h_i(0) = y_i, h_i(a) = y_i \frac{\sum_e m_i^E(e, a) \exp(r_i(a)e)}{\sum_e m_i^E(e, a)}
\]

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 (18). Wages can then be plugged into (3), (6), (7) and (8) to find \( J_i(e, a), E_i(e, a), U_i(e, a), N_i(e, a) \) as well as the surpluses defined by (17) for \( a \).

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

C Detailed calibration results

C.1 Reverse-engineered human capital profiles for college and non-college workers

We next describe the differences in human capital profiles between different education groups. Figure 13 shows, not surprisingly, that non-skilled groups have lower starting levels and growth rates of human capital compared to skilled. Also, human capital levels vary less between gender and race for non-skilled compared to skilled. Within race/ethnicity, males have higher levels of human capital over the life cycle for both skilled and non-skilled compared to females. Males also have steeper growth profiles of human capital: while for most male
Figure 13: Wage and human capital profiles over the life cycle for college and non-college workers, relative to the wage of 25 year old average White 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 than males – it keeps increasing over the whole life cycle. Stagnating human capital growth for certain female groups are likely related to career breaks: as many women leave the labor market during prime working ages due to family reasons, the average returns to experience for those groups is lower.

Within gender and education level, we also find fairly large differences in human capital profiles for different races/ethnicities, which increase over the life cycle. For non-skilled, White males and females have higher human capital levels over the whole life cycle compared to other races. For skilled, 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, 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 14 shows specifically the reverse-engineered returns to experience $(r_i(a))$ for both college and non-college workers. Returns to experiences gaps determine the gaps in the human capital growth rates. College-educated workers have higher $r_i(a)$ than non-college educated, as can be seen in the human capital profiles. Returns to experience seem to decrease for older workers, and this pattern is especially true for college-educated groups. Returns to experience
within non-college educated are the highest for White males and females followed by other male groups and Black females. In general, males have higher returns to experiences than females within race / ethnicity.

Figure 15 shows the wage-to-human capital profiles for different demographic groups, which represent the gross profits of firms hiring each demographic group. Gross-profits for a firm are higher for demographic groups who have lower long-time value of the match. The idea 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 u-shape for many groups: required profits are higher for younger workers, decreased for the prime-age workers, and then start increasing again towards the retirement. There is also gender and racial variation in the gross-profits for both non-college and college workers. Firms require lower gross-profits from males withing race, as their long-term value for a firm is likely to be higher. Only exception is Blacks, for whom the gross-profits for Black males are similar or even higher than for Black 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 all female groups converge. The patterns for college-educated females is very different: Asian females are now the group with notably higher gross-profits. It is likely arising from the fact that they have very high human capital and as the hiring costs are assumed to be increasing with 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 Black college-educated females have the lowest gross-profits. Among males, Black males again have the
highest gross profits. The gross-profits of White and Hispanics males are at the 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.

C.2 Reverse-engineered matching efficiencies for college and non-college workers

In general, matching efficiencies are higher for non-college groups than college groups (Figure 16). Non-college groups have more variation in the matching efficiencies compared to college groups. Also, the As of non-skilled males are decreasing relatively more with age compared to women and skilled men, which could reflect the fact that non-skilled males are more likely to be working in occupations requiring physical labor and aging is mattering more in these occupations.

Similarly as with human capital, males tend to have higher matching productivities within race and education compared to females. This is especially pronounced for non-skilled and younger workers. It is likely that younger female workers with lower education may be presumed less attached to labor market which then affect their job finding rate. Within skilled groups, the gender gap in matching efficiency for Blacks and Whites is quite small, and White females actually 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 wider gender gap compared to Blacks and Whites, but more modest than unskilled Hispanics.

When it comes to racial/ethnic differences in matching efficiencies, Hispanics
Figure 16: job-finding rates for unemployed and matching efficiencies over the life cycle for college and non-college workers.

Tend to do better in almost all gender-education groups: Hispanic males have the highest matching efficiencies among both skilled and non-skilled males, while the same is true for non-skilled Hispanic females. Within non-skilled 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 17 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 unemployed and nonparticipants, and that the search effort of unemployed is always 1. Thus, $\psi_N^Y(a)$ 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 labor force for various reasons, which is reflected in the lower job finding rate 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
Figure 17: Search effort, $\psi_N^{i}(a)$, of nonparticipants, skilled and non-skilled.

probability of finding a job decreases with age.

College-educated have higher search effort compared to non-college educated for all the other races/ethnicities except Asians. For Asians, the search effort for skilled and unskilled are quite similar, but the ordering varies over the life. There is also a gender gap in 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 effort for 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 (Source: US Census) and Black women are more likely to be single-mothers compared to other races, which then shows up as a higher attachment to labor force and a higher search effort of Black females. While Blacks have the lowest gender gap also among 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 education level, followed by Hispanics and Blacks, Black females have the highest search effort among females. Only for unskilled females, Asian and Hispanic females have higher search effort after age 40 than unskilled Black females. Whites have always the lowest search effort within a gender-education group.

Figures 18, 19, and 20 present the following estimated labor market flows: transition flows for average, as well as for the college and non-college workers between unemployment and non-participation, $\pi^{i\text{UN}}$, $\pi^{i\text{NU}}$, and job destruction rates for the college and non-college workers, $\pi^{i\text{EU}}$, $\pi^{i\text{EN}}$. 
Figure 18: Average transition flows between non-participation and unemployment (CPS 1998-2018).

Figure 19: Job destruction rates to unemployment and non-participation for college and non-college workers (CPS 1998-2018).
Figure 20: Transition flows between non-participation and unemployment for college and non-college workers (CPS 1998-2018).