Firm Heterogeneity and Racial Labor Market Disparities*

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Abstract

Black workers are more exposed to business cycle employment risk than white workers, even after adjusting for differences in industry and other factors. This paper shows that large employers play an outsized role in the excess sensitivity of Black employment, both in a variance decomposition with aggregate data and in micro-level regressions with individual controls. Motivated by this evidence, the paper develops and calibrates a search model with flexibly-specified racial disparities in hiring that vary with firm size. Large firms employ more Black workers, as in the data. In a slack labor market, Black employment is more negatively affected, as firms become more selective about hiring. This effect is amplified at large firms due to spillover effects on wages, though the relative contributions of large and small employers depend on the form of racial disparities. The preferred specification explains 45% of the empirical worsening employment gap and 72% of the share that comes from large firms.

JEL: E24, J63, J71, M51

Keywords: Racial employment gap, firm heterogeneity, worker heterogeneity

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1. Introduction

The Black population in the U.S. faces persistently lower rates of employment than the white population. Additionally, Black employment responds more to macroeconomic conditions, rising more during expansions but also falling more during contractions. For example, over the peak to trough of the Great Recession, the Black employment rate fell by 4.5 percentage points whereas the white employment rate fell by 3.2 percentage points. Observable worker characteristics are unable to explain either the level of the employment gap or its movements over the business cycle, as shown in Figure 1a. Understanding differences in exposure to aggregate labor market risk is important both for addressing persistent racial economic disparities and also for designing equitable stabilization policies in response to downturns.

This paper explores the role of firm heterogeneity and disparities in hiring for explaining the greater sensitivity of Black employment to macroeconomic conditions. Black workers are about 5.6 percentage points more likely to be employed by large firms than white workers, conditional on observable characteristics such as industry and location, as illustrated in Figure 1b.[1] Motivated by these differences in compostion, I document new facts about aggregate employment volatility and individual-level employment transitions by race and firm size. The main takeaway of my analysis is that large firms are particularly important for the fluctuations in Black employment over the business cycle. I show that these patterns are consistent with a model in which Black and white workers are ex-ante identical, but Black workers face a lower matching rate, particularly at small firms. The model reveals that Black employment is more responsive to changes in aggregate productivity under several assumptions about the source of hiring disparities by race. The relative contributions of large and small firms depend on the type of disparity and the size of spillover effects between small and large firms. This has two relevant takeaways for policy. First, policies that aim to reduce discrimination by regulating the largest firms may be less effective if the spillover effects from small firms are sufficiently large.[2] Second, policies that target small firms may

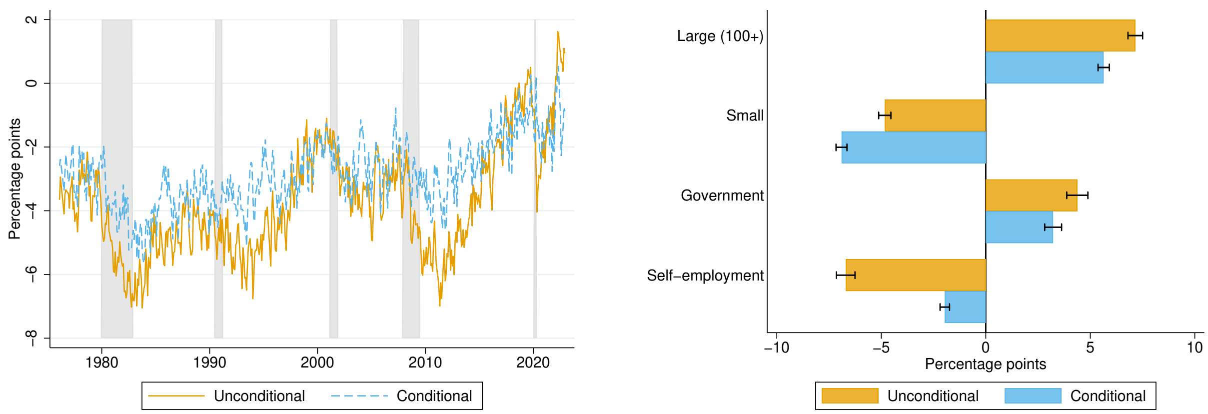
[1] Mean employment at firms with 100 or more employees for Black workers is 51% in the March supplement to the CPS and 52% in the SIPP.

[2] For example, firms with 100 or more employees (or government contractors with 50 or more employ-

Figure 1: Racial gaps in employment and employer composition

(a) Employment-population ratio Black-white

(b) Share of workers by employer type Black-white



The solid line in Panel (a) reports the difference in employment-population ratios between Black and white populations over the population 20 and older in the CPS. The dashed line reports the unexplained gap from a Oaxaca-Blinder decomposition estimated separately in each period, with controls for age; age-squared; gender interacted with marital status; education; state; metro area size; modal industry and occupation. Panel (b) reports the difference between the composition of Black and white employed workers, using the March supplement to the CPS. The blue bars report the residual gap after conditioning on the same set of controls as Panel (a) with fixed effects for year. Large firms have 100 or more employees.

be less effective at stabilizing employment for the Black population due to both composition effects and the importance of fluctuations at large firms.[3]

The paper starts by using aggregate data from the Quarterly Workforce Indicators and a variance decomposition to quantify the contributions of large and small firms to the excess volatility of Black employment relative to white. I find that sorting patterns mechanically explain at most 3 percent of this gap, with the remainder coming from excess volatility of Black employment at large and small firms. Black employment at large firms is especially volatile, contributing at least 5.3 percent more to the excess volatility than would be expected based on the relative share of Black employment. This excess volatility of large firms is also apparent in hires and separations.

Next, using micro-data from the Survey of Income and Program Participation, I show

ees) must report the composition of their workforce by occupation to the Equal Employment Opportunity Commission (EEOC) each year.

[3]For example, the Paycheck Protection Program incentivized employee retention at small firms during the Covid-19 recession.

that Black employment and hiring are more sensitive to labor market conditions, even within individuals. When the state-level unemployment rate is 1-standard-deviation higher, Black workers are an additional 0.6 percentage point less likely to be employed than white workers, controlling for worker fixed effects. This change represents about 8% of the unconditional mean employment gap and is driven by the change in employment at large firms. I observe similar patterns in total hiring and job-finding from nonemployment as well, though not in separations.

The empirical patterns show that Black workers are more likely to work for large firms and that large firms contribute more to the worsening of the employment gap when the labor market is weak. I next develop a model to study how racial disadvantages in the hiring process across firms contribute to these patterns. I start with a canonical random search model and introduce three main ingredients: endogenous firm size, uncertain worker productivity, and racial disadvantages in hiring. The first two ingredients create a trade-off for firms between recruiting intensity and selectivity. If firms choose a high selectivity strategy, they pay high search costs but the workers they recruit are very likely to be productive so the cost of turnover is lower. I assume that small firms face higher search costs than large firms, which implies that the benefit of screening workers is lower for small firms and they will choose a lower selectivity strategy.[4] This produces higher turnover rates at small firms.

The third ingredient is the assumed disadvantage for Black workers in hiring. Any assumption will undoubtedly fail to capture the full set of factors that differentially affect labor market outcomes for Black relative to white workers, such as such as employer prejudice (Charles & Guryan, 2008), intergenerational wealth (Toney & Robertson, 2021), risk of incarceration (Pettit & Western, 2004), to name just a few. I take a general approach in which I calibrate the model under three alternative assumptions about the nature of these disparities and compare the results across specifications. In the simplest, preferred specification, I assume Black workers receive fewer matches than white workers, for purely exogenous reasons. This simulates a callback gap (e.g. Bertrand & Mullainathan, 2004,

[4]This is consistent with evidence that small firms interview fewer candidates per hire (Barron *et al.*, 1997).

Kline *et al.*, 2022, etc.), without taking a stance on the reason for the gap. In the second version of the model, I assume that firms receive noisier signals about Black applicants, particularly at small firms. This operates similarly to a statistical discrimination model, and is meant to capture differences in workers' professional networks leading to variation in the quality of information about applicants, as documented by Miller & Schmutte (2023). In the final specification, I embed taste-based discrimination, with the assumption that small firms are more likely to discriminate. This would be consistent with small firms facing less legal scrutiny from the EEOC. With statistical discrimination, firms find fewer Black workers who meet their productivity criteria, whereas with taste-based discrimination they find fewer Black workers who meet their inflated standards for hiring. In both cases, this generates lower employment for Black workers and sorting towards large firms.

Finally, I calibrate the model to match moments from the micro-data and simulate a counterfactual, low aggregate productivity economy, meant to mimic the high-unemployment periods in the data. The model predicts that the racial employment gap worsens with lower aggregate productivity, explaining 45% of the total worsening of the employment gap from data in the simplest model. Decreased demand for labor leads to a decrease in market tightness, allowing firms to attract more applicants per unit of search intensity. Thus, firms substitute more towards a high selectivity strategy, which reduces the surplus they share with workers in wages. This has an outsized effect on employment for Black workers, because this rate is affected by both the increase in selectivity as well as general equilibrium changes in relative wages. Across all three specifications of racial disparities, the racial employment gap worsens in the low productivity steady state, with more severe outcomes in the discrimination models. The relative contributions of large and small firms to this worsening depends on the form of racial disparities. The callback gap model captures the outsized impact of large firms, whereas the discrimination models have a more prominent role for small firms. Understanding the underlying disparities in the labor market is therefore important for targeted policies seeking to stabilize employment during downturns.

Related literature This paper contributes to several major strands of the literature. First, there is an extensive literature studying the excess sensitivity of Black employment to macroeconomic conditions (Couch & Fairlie, 2010; Hoynes *et al.*, 2012; Cajner *et al.*, 2017; Aaronson *et al.*, 2019; De *et al.*, 2021; to name a few). My finding that the job-finding margin is the most responsive for Black workers during downturns is consistent with recent evidence by Forsythe & Wu (2021) and Kuhn & Chancí (2021). Another related area of research considers the effects of monetary policy on racial inequality (see Bartscher *et al.*, 2021; Lee *et al.*, 2022; Bergman *et al.*, 2020; Thorbecke, 2001; Carpenter & Rodgers III, 2004; Zavodny & Zha, 2000). This literature demonstrates the policy interest of understanding how racial differences evolve over the business cycle. My paper contributes to this literature by introducing the role of employer heterogeneity, which is interesting on its own for understanding how shocks permeate through the economy, but also could have important implications for economic policies that interact with the firm size distribution.

Second, there is a large micro literature documenting racial disparities and discrimination in the labor market (see Lang & Lehmann (2012) for an overview). The fact that Black workers are more likely to be employed by large firms was documented by Holzer (1998) and has more recently been emphasized by Miller (2017) and Miller & Schmutte (2023). In the statistical discrimination literature, Morgan & Várdy (2009) shows that if firms are sufficiently selective, then differences in "discourse systems" that make it harder for firms to evaluate minority workers will lead to underrepresentation of minorities. Miller & Schmutte (2023) uses this framework to show that differences in referral networks can lead minority workers to disproportionately sort to large firms (Okafor (2022) highlights a similar mechanism without firm size). More generally, a large-scale correspondence study by Kline *et al.* (2022) finds that callback gaps on the basis of perceived race are prevalent even among the largest employers, though the gaps are somewhat smaller than those found in other studies, such as Bertrand & Mullainathan (2004). Banerjee *et al.* (2018) also finds less discrimination among larger employers in Canada. My paper builds on these studies by incorporating heterogeneous discrimination by firm size in a search model. I use different specifications to study how the results vary with the form of discrimination. I also show that endogenous wages are important for understanding joint disparities in hiring and wages.

Finally, the macro literature has studied the role of firm heterogeneity in labor market fluctuations. Empirically, Moscarini & Postel-Vinay (2012) and Haltiwanger *et al.* (2018) show the importance of job creation at large firms for aggregate employment fluctuations. Other papers have introduced firm heterogeneity and endogenous size in the canonical random search model (Elsby & Michaels, 2013, Acemoglu & Hawkins, 2014, Fujita & Nakajima, 2016), and shown that information frictions are important in this context (Baydur, 2017). My paper extends these findings to embed worker group heterogeneity and statistical and taste-based discrimination frameworks.

2. Empirical Evidence

This section studies how employment patterns by race and firm size vary with macroeconomic conditions. Section 2.1 uses aggregate data by race and firm size to show that most of the excess employment volatility for Black workers comes from volatility at large firms. Section 2.2 shows that these patterns are persistent in worker-level data, after controlling for individual characteristics.

2.1. Macro-level Empirical Patterns

Data The Quarterly Workforce Indicators (QWI) data are public-use aggregates made available by the U.S. Census Bureau from linked employer-employee microdata. They include quarterly employment, job creation, job destruction, average earnings, and other measures of employment flows that are available at several levels of disaggregation on both firm and worker characteristics. I focus on the statistics by race and firm size from 2001Q1 to 2019Q4.[5]

Decomposition of employment volatility I start with the seasonally-adjusted time series of log employment for Black and white workers, and detrend it with an HP-filter.

[5] The national QWI data start in 1993Q2, but national statistics are derived from state-level data, where the state coverage is increasing over time. In 1993, state-level data are available for roughly 20% of states (likely less by population), rising to over 80% by 2001. QWI statistics by race/ethnicity and firm size cannot be combined with any other worker characteristics, such as gender, age, or education, or with firm age.

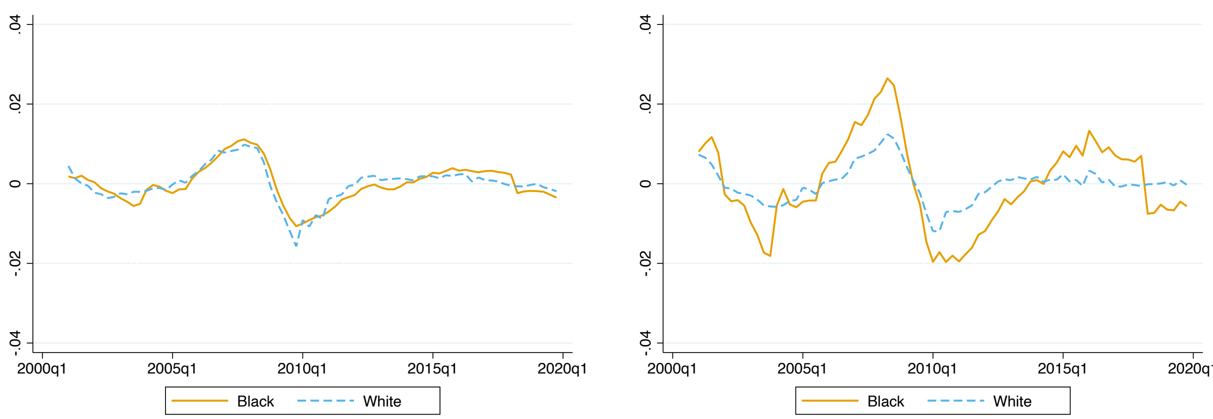
Consistent with the employment gap shown in Figure 1a, Black employment is more volatile than white employment, with a standard deviation of 0.016 log point, relative to 0.009 log point.[6] I use the time series of employment by firm size to decompose total employment deviations from trend into the contributions of large and small employers. First, I log-linearize total employment to decompose it into firm-size components,

$$\log e_{gt} - \log \bar{e}_{gt} = \sum_j (\log e_{jgt} - \log \bar{e}_{jgt}) \times \frac{\bar{e}_{jgt}}{\bar{e}_{gt}}, \tag{1}$$

where $\bar{e}$ is the time trend in employment, g indexes race, t is quarter, and j is firm size. Figure 2 show the contributions of small and large firms to detrended aggregate employment, which is the sum of both panels. Panel (a) shows that the total contribution of small firms is relatively similar for Black and white workers, while Panel (b) shows that large firms contribute significantly more to the fluctuations in employment for Black workers.

Figure 2: Employment volatility by firm size

(a) Small-firm contribution **(b)** Large-firm contribution



This figure shows the decomposition terms from Equation 1 for HP-filtered log employment for Black and white workers. The two panels sum to the aggregate detrended employment across all sizes. Large firms have 250 or more employees. The units are log deviations from trend.

The difference in the contributions of large and small employers to Black and white employment fluctuations depends both on the size-specific employment fluctuations and the

[6]Using a linear trend instead these standard deviations are 0.033 and 0.018 log points, respectively.

share of workers employed at each type of firm. Table 1 Panel (a) reports the large-firm share of employment for Black and white workers. Large firms could contribute more to Black employment fluctuations because they are more volatile and Black workers are more likely to be employed by large firms, so they are more exposed to this volatility. To disentangle this effect, I perform the following decomposition of the Black-white employment gap,

$$\tilde{e}_{Bt} - \tilde{e}_{Wt} = \underbrace{\sum_j \tilde{e}_{jWt} \times \left(\frac{\bar{e}_{jBt}}{\bar{e}_{Bt}} - \frac{\bar{e}_{jWt}}{\bar{e}_{Wt}} \right)}_{\text{Composition}} + \underbrace{\sum_j \left(\tilde{e}_{jBt} - \tilde{e}_{jWt} \right) \times \frac{\bar{e}_{jBt}}{\bar{e}_{Bt}}}_{\text{Excess volatility}}, \tag{2}$$

where $\tilde{x}_t = \log(x_t) - \log(\bar{x}_t)$. I use this equation to perform a variance decomposition of the detrended employment gap between Black and white workers, which has a standard deviation of 0.009 log point. Results are reported in Table 1 Panels (b) and (c). With the HP-filter trend, 3% of the variance can be explained by the composition effects, whereas the excess volatility of Black employment at large and small firms contribute 74% and 24%, respectively. To remove the scaling effects, that large firms have a higher Black share of employment and therefore are likely to make a bigger contribution, I first calculate the total excess volatility term in brackets in Equation 2. Then I subtract the contribution that would be expected if the total excess volatility were distributed according to the employment shares from each terrm. The large firm excess volatility contribution is thus 6.4 percentage points higher than its proportional share of the total excess volatility term. Using a linear trend, composition makes a small negative contribution and the excess contribution of large firms is smaller but still sizeable at 5.3 percentage points.

I also apply Equation 2 to total gaps in hires and separations, which have standard deviations of 0.025 and 0.023 log deviations from trend.[7] Composition effects make larger positive contributions for hires and separations than for total employment, though the error of these decompositions is higher for the HP-filter specification. The excess volatility of large firms is also larger for hires and separations across both specifications.

[7]With the linear trend, these are both 0.05 log points.

Table 1: Employment shares and variance decomposition

(a) Large firm share

	Black	White
Employment	69.4	53.9
Hires	63.9	47.4
Separations	64.9	48.7

(b) Variance decomposition, HP-filter

	Composition	Excess large	Error
Employment	3.3	6.4	-0.6
Hires	10.6	8.2	1.1
Separations	8.9	8.5	2.7

(c) Variance decomposition, linear trend

	Composition	Excess large	Error
Employment	-1.1	5.3	-0.3
Hires	5.0	7.8	0.4
Separations	5.7	7.3	0.7

Panel (a) reports the large-firm (250 employees or more) share of employment, hires, and separations for Black and white workers in the QWI. Panels (b) and (c) report the variance decomposition using equation 2 with different trend estimates. The excess volatility term is is the contribution of large firms in excess of their relative share of employment, hires, or separations. The units are percentage points.

2.2. Micro-level Empirical Patterns

The previous section showed that excess fluctuations in employment, hires, and separations at large firms are important for understanding aggregate differences in the variance of these outcomes between Black and white workers. In this section, I use micro-level data to study employment and turnover patterns with controls for individual worker characteristics.

Data I use data from the Survey of Income and Program Participation (SIPP), which provides high-frequency information on workers' transitions between employment states and employer types in combination with details about worker occupations, education, and other characteristics. The SIPP is a rotating panel that interviews households every four months for approximately 3-4 years. I use data from the 1996, 2001, 2004, and 2008 panels.[8] I focus on individuals aged 20 or older who self-identify as non-Hispanic white or Black.

In order to study differences in employment rates and transition rates by employer type, I start by assigning each person to a monthly labor force state using their labor force status for the week corresponding to BLS convention, as described by Fujita *et al.* (2007). I

[8]For the 2008 panel, I only use waves 1-10 of 16 due to a change in the firm size survey instrument. See Online Appendix A.1 for details on the construction of firm size and the discrepancy in the later waves of the 2008 panel.

first assign workers as either employed or nonemployed (either unemployed or out of labor force). I focus on nonemployment because I observe a substantial number of transitions from inactivity to employment that I do not want to exclude.[9] To capture the segment of the population that is reasonably attached to the labor force, I exclude individuals who are inactive over the full SIPP panel (3-4 years). The SIPP has a well-documented issue of seam bias, whereby respondents are more likely to report transitions over the months between survey waves (Moore, 2008). Because one-quarter of respondents are at the seam in each month, this bias should not contaminate the analysis but I perform robustness to dropping observations at the seams.

For employed individuals, I use job and business history information to match employer characteristics to employment status. I assign each employed worker-month observation to one of four mutually exclusive employer classifications: large firm, small firm, government, or self-employed. Large firms have 100 employees or more, as firm size above this threshold is not further disaggregated during my sample period. For workers who are simultaneously employed by two jobs, I select the job that has higher hours, with longer tenure as a tie-breaker. I only classify a worker as self-employed if they do not work for another employer during that month. I am able to classify 99% of workers to their employer type.[10]

I use job start and end dates to identify hires and separations. I define a hire as a person who meets one of the following criteria: reports a job start date in the current month or was nonemployed in the previous month and employed in the current month. I define a large-firm hire and a small firm hire in the same manner, restricting to large and small firms. Based on these criteria, I observe approximately 167,000 hires, with 51% large-firm hires, 38% small-firm hires.

Similarly, I define a separation as a job with an end date in the current month, or a person employed in the current month but nonemployed in the following month. I classify separations as either voluntary or involuntary based on the reason given for the job ending.[11]

[9] Roughly half of all nonemployment-to-employment transitions are from unemployment.

[10] This classification is not 100% because some workers have more than two employers over the four month survey period so I only observe the two that they choose to describe in the interview, or there may be inconsistencies in the start/end dates.

[11] Reasons for involuntary separations include: on layoff, discharged/fired, employer bankrupt, employer

I also classify separations that I do not observe end dates for as involuntary if the worker is unemployed in in the following month (not inactive). I observe approximately 155,000 separations, with 51% and 38% at large and small firms. 43% of separations are categorized as involuntary. Online Appendix A.1 provides additional summary statistics.

Cyclical changes in employment by race and firm size In this section, I study how employment by race and firm size varies with aggregate conditions in the economy. I start with a linear probability model of employment, with the following specification,

$$E_{ijt} = \alpha_j + \alpha_j^B \text{Black}_i + \beta_j \text{UR}_t + \beta_j^B \text{Black} \times \text{UR}_t + \Gamma_j X_{ijt} + \epsilon_{ijt}, \tag{3}$$

where E_{ijt} is an indicator equal to 1 if worker i is employed at a type-j firm in month t; Black_i is a racial dummy variable; UR_t is the state-level unemployment rate in month t with units standardized; and X_{it} is a vector of worker characteristics. Worker characteristics are age; age-squared; marital status interacted with gender; education; geographic region; an indicator for large metro area; modal occupation and industry. I cluster standard errors by person and time. I run this regression separately for each employer-type outcome, so the sample is always the same set of workers but the outcome of interest changes. The total employment rate is equal to the sum of the employer-specific rates.

The results are reported in Panel (a) of Table 2. Black workers face lower employment rates relative to white workers with similar characteristics, with the vast majority of the gap arising from small firms, consistent with Figure 1. When the state unemployment rate is 1-standard-deviation higher, the probability of employment decreases across all types of employers. For Black workers, the employment probability decreases by an additional 0.4 percentage point. This additional decrease is driven by large and public employers, though the difference is not statistically significant for large firms.

Given the panel structure of the SIPP, I can analyze how changes in the state unemploy-

sold business, job was temporary and ended, slack work or business conditions.

Table 2: Employment fluctuations by firm type

(a) Individual controls

	(1) All	(2) Large	(3) Small	(4) Government	(5) Self
Black	-4.08	2.65	-7.31	2.73	-2.04
	(0.22)	(0.31)	(0.25)	(0.22)	(0.17)
UR	-1.20	-0.52	-0.50	-0.06	-0.14
	(0.13)	(0.13)	(0.11)	(0.08)	(0.09)
Black × UR	-0.64	-0.42	0.24	-0.70	0.22
	(0.21)	(0.28)	(0.21)	(0.19)	(0.15)
R2	0.069	0.168	0.063	0.387	0.130
N	5,967,568	5,967,568	5,967,568	5,967,568	5,967,568
Black mean	75.87	39.46	14.88	16.32	4.55
White mean	83.88	37.30	21.87	13.20	10.49

(b) Individual fixed effects

	(1) All	(2) Large	(3) Small	(4) Government	(5) Self
UR	-1.49	-1.30	-0.30	0.03	0.02
	(0.27)	(0.16)	(0.11)	(0.07)	(0.06)
Black × UR	-0.64	-0.62	0.27	-0.34	0.16
	(0.29)	(0.27)	(0.25)	(0.16)	(0.12)
R2	0.573	0.739	0.681	0.854	0.829
N	6,097,293	6,097,293	6,097,293	6,097,293	6,097,293
Black mean	75.87	39.46	14.88	16.32	4.55
White mean	83.88	37.30	21.87	13.20	10.49

The table reports differences in employment probability by race and macroeconomic conditions. The units are percentage points. UR is the state-level unemployment rate expressed in standard deviations from the mean. Panel (a) includes controls for age; age-squared; marital status interacted with gender; education; state; metro area size; modal industry and occupation. Panel (b) includes individual fixed effects. Standard errors are clustered by person and month.

ment rate affect employment outcomes within individuals using a fixed effects specification,

$$E_{ijt} = \alpha_{ij} + \beta_j \mathrm{UR}_t + \beta_j^B \mathrm{Black} \times \mathrm{UR}_t + \epsilon_{ijt}, \tag{4}$$

where again, the sample is always the same but the outcome variable of interest changes with employer type. I cluster standard errors by person and time. The coefficients on the unemployment rate should pick up differences in the timing of employment within person.

The results are shown in Panel (b) of Table 2. The effect of aggregate conditions on employment probability is slightly larger with individual fixed effects. A 1-standard-deviation increase in the state unemployment rate is associated with a 1.5 percentage point decrease in the probability of employment for white workers and a 2.1 percentage point decrease for Black workers. The excess reduction in employment is concentrated among large firms, especially for Black workers. Black workers face an additional 0.6 percentage point reduction in employment at large firms. Online Appendix A.2 shows that these results are robust to including additional interaction terms.

Hiring and separation patterns Next, I consider patterns in hiring and separation by race and firm size. To get at the population-wide patterns comparably to the QWI data, I start with the same linear probability model as Equations 3 and 4, with the outcome variable equal to 1 if person i is a new hire in month t. This specification is distinct from studying job-finding rates, and instead is meant to show how aggregate flows in the total number of hires vary with aggregate conditions, conditional on individual characteristics. It will capture both changes in job-finding rates as well as changes in the composition of employment, since it does not condition on a person's employment status. The results are shown in Table 3 Panel (a). Within individuals (columns 4-6), hiring is sensitive to the state unemployment rate, with the probability falling 0.14 percentage point for white workers, and an additional 0.23 percentage point for Black workers. This sensitivity of hiring to aggregate conditions is concentrated among large firms, with the hiring probability decreasing 0.14 percentage point, the same as the aggregate effect, and and additional 0.15 percentage point decrease for Black workers.

Table 3 Panel (b) reports variation in job-finding rates, rather than aggregate hiring. Columns (1)-(3) restrict the sample to individuals who were nonemployed in the previous month or who are coded as nonemployed in the current month but report starting a job in this month. Columns (4)-(6) do the same for unemployment. Similar to the results for aggregate hiring rates, job-finding rates decrease when the state unemployment rate is 1-standard deviation higher. Job-finding from nonemployment decreases more for Black

Table 3: Job inflows by firm type

(a) Hires (percent of population)

	(1) All	(2) Large	(3) Small	(4) All	(5) Large	(6) Small
Black	0.04	0.32	-0.31			
	(0.04)	(0.03)	(0.02)			
UR	-0.11	-0.08	-0.05	-0.14	-0.14	-0.02
	(0.03)	(0.02)	(0.01)	(0.10)	(0.05)	(0.03)
Black × UR	-0.08	-0.10	0.01	-0.23	-0.15	-0.09
	(0.03)	(0.03)	(0.02)	(0.08)	(0.06)	(0.04)
R2	0.011	0.007	0.006	0.075	0.069	0.068
N	5,967,568	5,967,568	5,967,568	6,097,293	6,097,293	6,097,293
Black mean	3.05	1.85	0.90	3.05	1.85	0.90
White mean	2.65	1.32	1.03	2.65	1.32	1.03
Individual FE				X	X	X

(b) Job-finding

	(1) All	(2) Large	(3) Small	(4) All	(5) Large	(6) Small
Black	-2.13	0.09	-2.01	-8.07	-2.22	-5.17
	(0.19)	(0.13)	(0.10)	(0.42)	(0.32)	(0.24)
UR	-1.14	-0.64	-0.43	-5.27	-2.86	-2.01
	(0.18)	(0.09)	(0.07)	(0.26)	(0.16)	(0.13)
Black × UR	-0.18	-0.28	0.11	1.63	0.27	1.25
	(0.15)	(0.11)	(0.08)	(0.30)	(0.23)	(0.16)
R2	0.027	0.021	0.016	0.036	0.026	0.022
N	906,071	906,071	906,071	223,203	223,203	223,203
Black mean	9.68	5.63	2.79	16.69	10.08	4.84
White mean	11.60	5.40	4.32	24.59	12.17	9.41
Unemployed sample				X	X	X

The table reports differences in hiring rates by race and macroeconomic conditions. The units are percentage points. UR is the state-level unemployment rate expressed in standard deviations from the mean. Panel (a) includes all individuals and panel (b) restricts to nonemployed or unemployed individuals. All columns without fixed effects include controls for age; age-squared; marital status interacted with gender; education; state; metro area size; modal industry and occupation. Standard errors are clustered by person and month.

workers at large firms, with Black workers experiencing an additional 0.28 percentage point decrease in the large-firm job-finding probability. In the unemployment specification, the job-finding rate decreases by a much larger 5.3 percentage points for white workers when the state unemployment rate is 1-standard-deviation higher. For Black workers, the decrease in job-finding with increases in state unemployment is smaller, though there is a much larger gap on average. Most of the attenuation comes from small firms, indicating that for Black workers, the gap in job-finding at large firms is relatively more consequential when unemployment is high relative to when it is lower.

Table 4 reports results for separation rates, where I estimate equation 3 on the sample of workers employed in the current month. The outcome variable in columns (1)-(3) is an indicator for any separation between the current month and the next month, and columns (4)-(6) resrict the outcome variable to involuntary separations. The involuntary distinction is important for the aggregate coefficient on the unemployment rate, with columns (1)-(3) having small, negative, and statistically insignificant coefficients, while columns (4)-(6) have larger positive coefficients. Across specifications, the Black-unemployment interaction term is negative and not statistically different from zero. Thus, in the SIPP data, separations for Black workers do not appear to be more sensitive to aggregate unemployment, though the overall Black-white separation gap is large. Separations for Black men are weakly more responsive to aggregate unemployment, as shown in Online Appendix A.3.

3. Model

The empirical results demonstrate that Black employment is more sensitive to aggregate conditions than white employment, particularly at large firms, in excess of what would be predicted by worker characteristics. We see this pattern in both aggregate employment and hires. In this section, I develop a model that embeds heterogeneous advantages in the hiring process as a mechanism for contributing to these patterns. The model features heterogeneous firms, heterogeneous workers, and a frictional labor market. It is set in discrete time.

3.1. Environment

Workers A unit mass of infinitely-lived workers are endowed with one indivisible unit of labor. They share a common discount factor, β, with linear preferences for consumption.

Table 4: Separation rates by firm type

	(1) All	(2) Large	(3) Small	(4) All	(5) Large	(6) Small
Black	0.26	0.40	0.51	0.35	0.45	0.52
	(0.05)	(0.06)	(0.11)	(0.03)	(0.04)	(0.07)
UR	-0.03	-0.05	0.00	0.18	0.18	0.29
	(0.04)	(0.04)	(0.05)	(0.02)	(0.03)	(0.03)
Black × UR	-0.03	-0.10	0.03	-0.01	-0.00	-0.04
	(0.04)	(0.06)	(0.10)	(0.03)	(0.04)	(0.08)
R2	0.012	0.013	0.010	0.006	0.006	0.006
N	4,826,652	2,291,178	1,283,686	5,050,241	2,291,178	1,283,686
Black mean	6.61	6.66	10.58	3.07	2.84	4.76
White mean	3.17	3.05	4.08	1.27	1.23	1.79
Involuntary				X	X	X

The table reports differences in separation rates by race and macroeconomic conditions. The units are percentage points. Columns (1)-(3) include all separations and columns (4)-(6) restrict the outcome variable to involuntary separations. UR is the state-level unemployment rate expressed in standard deviations from the mean. All columns include controls for age; age-squared; marital status interacted with gender; education; state; metro area size; modal industry and occupation. Standard errors are clustered by person and month.

They produce and consume a single homogeneous good. Workers have no disutility of labor but may be unemployed due to frictions in the labor market. Let u_t denote the mass of unemployed workers at the start of period t (with $1 - u_t$ the mass of employed workers). Unemployed workers receive flow utility b. Firms are owned by workers with dividends distributed in lump sum.

There are two types of workers, $g \in \{W, B\}$, corresponding to white and Black, with (a fixed) fraction $\pi < \frac{1}{2}$ in B. The only assumed difference across worker groups is that Black workers face a disadvantage in hiring that can vary by firm size. Rather than choose one source of this disadvantage, I present three general alternatives: (1) Black workers receive matches at a lower rate than white workers for exogenous reasons (meant to capture a callback gap from the correspondence study literature); (2) firms receive noisier information about Black candidates, as in the statistical discrimination literature; (3) firms have a disutility for employing Black workers, as in the taste-based discrimination literature. For comparison, I also discuss a baseline model with no differences across worker groups.

Firms There are two types of firms indexed by their idiosyncratic productivity z, which I assume to be fixed. They share a common aggregate productivity a. They use labor to produce a single good with decreasing returns to scale production technology,

$$y = azn^{\alpha}.$$

Differences in productivity with decreasing returns to scale generates large and small firms. Firms also differ in their recruiting costs, described below.

Matching and hiring process This is a random search model with information frictions in the hiring process (Baydur, 2017, Jarosch & Pilossoph, 2019). Firms post vacancies (v) to attract matches at cost $c_v(z)$, which varies with firm productivity. Vacancy posting can be interpreted as recruiting intensity. The more vacancies the firm posts, the more candidates it has to choose from when deciding who to hire. The matching rate between vacancies and unemployed workers depends on market tightness, θ, where the probability that a vacancy attracts a worker is $q(\theta)$, the probability an unemployed worker meets a firm is $\theta q(\theta)$, and $\theta = \frac{V}{U}$ is market tightness. Given that this is random search, workers do not target particular types of firms and firms cannot target their vacancies to particular workers. A worker matches to a type z firm proportional to their share of vacancies, while a firm matches to a type g worker proportional to their share in the unemployed pool.

In the model with an exogenous callback gap (alternative 1), these proportions are exogenously distorted such that Black workers receive fewer matches than white workers, and they may receive proportionally more matches from large firms. The probability that a vacancy posted by a type z firm receives a match from group g is $\lambda_{gz}\frac{u_g}{u}q(\theta)$, where u_g is the number of unemployed workers from group g and λ_{gz} governs the degree of distortion. This is the most general alternative as it does not impose a reason for the lower match rate for Black workers, but captures the empirical fact that Black workers receive fewer responses to applications than white workers (see for example, Bertrand & Duflo, 2017).

When workers and firms meet, both parties face uncertainty around the worker's productivity, which is revealed at the production stage if the worker is hired. Workers can either be a productive type, contributing one unit of labor to the firm's production function, or unproductive, contributing zero. Each time a worker meets a firm, they draw a new match quality from the same distribution, $F(\cdot)$, which determines the likelihood the worker will be productive.[12] Match quality is unobservable to the worker and the firm, but both observe a signal of match quality, s. The signal follows the inspection technology form of Menzio & Shi (2011), where the firm observes the true match quality with probability p. With probability $1-p$, the firm observes another i.i.d. draw from the same distribution. Thus, the firm forms a posterior belief (x) about the worker's productivity conditional on their signal, according to

$$x = ps + (1-p)\mathbb{E}[s]. \tag{5}$$

In the statistical discrimination case (alternative 2), this probablity can vary by race and firm type, p_{gz}. The assumption is that Black workers face a lower p_{gz}, particularly at small firms (low z). This is equivalent to assuming that hiring managers place more weight on the population mean than the individual's qualifications when screening Black workers, as in the statistical discrimination literature (e.g. Black, 1995, Lang & Lehmann, 2012). This assumption can also capture differences in referral networks that affect the information firms have about potential hires, as in Miller & Schmutte (2023).

Using these beliefs, the firm must decide which matches to hire. The firm chooses a group-specific threshold rule, x_g^* such that it hires all matches from that group with expected productivity above the threshold. Once workers are hired, wages are bargained using Stole & Zwiebel (1996) and then wages are paid, production occurs, and new hire types are revealed.

In the taste-based discrimination case (alternative 3), taste costs, χ_{gz}, are paid at this stage for all incumbent workers and new hires. These costs are assumed to be larger for Black workers, especially at small firms. This could arise if small firms have stronger preferences

[12] This set-up follows Baydur (2017) to create a learning model similar to Jovanovic (1979) in which all uncertainty is resolved within the first period. This creates a distribution of types in the hiring stage without having to keep track of a distribution of types in the state space.

for hiring workers of the same race, given the higher prevalence of white-owned businesses (Miller & Schmutte, 2023). It could also reflect the lower scrutiny that small employers face from the Equal Employment Opportunity Commission (EEOC), perhaps allowing more scope for taste-based discrimination.[13]

At the start of the next period, all of the unproductive hires from the end of the previous period separate and an exogenous share δ of the productive hires separate. These newly separated workers are not able to search until the following period.

3.2. Optimization

Firm's Problem The firm chooses vacancies, v, and hiring standards, $\{x_g^*\}$, which implicitly define the number of hires, $\{h_g\}$, the expected productivity of hires, $\{\bar{x}(x_g^*, p_{gz})\}$, and next period employment, $\{n_g'\}$ for each group. The idiosyncratic states are the number of incumbent workers from each group and fixed firm productivity, z. The aggregate state space is rich. It includes aggregate productivity, a, market tightness, θ, and other distributional features of the economy, such as the Black share of unemployed workers. To ease notation, I use the subscript t to summarize the aggregate states in the firm's value function,

$$\begin{aligned} J_t(n_B, n_W, z) = \max_{v \geq 0, x_g^*} & - c_v(z)v + a_t z(n')^\alpha - \sum_g \left((1-\delta)n_g + h_g\right)\chi_{gz} \qquad (6) \\ & - \sum_g \big((1-\delta)n_g w_t^n(n', z, g) + h_g w_t^h(x_g^*, n', z, g)\big) + \beta \mathbb{E}_t J_{t+1}(n_B', n_W', z) \\ & \text{s.t.} \\ & n' = \sum_g n_g' \qquad (7) \\ & n_g' = (1-\delta)n_g + \bar{x}(x_g^*, p_{gz})h_g \qquad (8) \\ & h_g = \lambda_{gz}\frac{u_{gt}}{u_t}q(\theta_t)v(1 - F(x_g^*|p_{gz})) \qquad (9) \\ & (1-p_{gz})\mathbb{E}[x] \leq x_g^* \leq p_{gz} + (1-p_{gz})\mathbb{E}[x] \qquad (10) \end{aligned}$$

[13] One interpretation could be that the taste costs are net of penalties, which are likely lower for small firms, as the EEOC tends to prioritize its limited resources for large firms.

where $w_t^n(\cdot)$ and $w_t^h(\cdot)$ are wages paid to incument workers and new hires, respectively. These wages are determined by bargaining and may depend on aggregate and idiosyncratic states.[14] Equation 10 reflects the bounds of posterior belief formation from equation 5 with the signal ranging from 0 to 1. $F(x|p)$ and $\bar{x}(x,p)$ capture features of the distribution of posterior beliefs a firm forms about match productivity, given the quality of the signal, p, and the exogenous distribution of match productivity, $F(\cdot)$. $F(x|p)$ is the cumulative distribution of posteriors conditional on signal quality p,

$$F(x|p) = F\left(\frac{x-(1-p)\mathbb{E}[x]}{p}\right), \tag{11}$$

where $F(\cdot)$ is the exogenous distribution of match quality. $\bar{x}(x,p)$ is the expected productivity of a hire conditional on a hiring threshold of x,

$$\bar{x}(x,p) = \frac{\int_{y\geq x} y dF(y|p)}{1-F(x|p)}. \tag{12}$$

Vacancy costs are linear but I allow the vacancy cost to vary with fixed firm productivity, z, with the assumption that $\frac{\partial c_v(z)}{\partial z} < 0$. Thus firms with higher productivity, which will be endogenously larger, have lower vacancy costs. In a two-firm model, this specification delivers the intuition that larger firms can have larger human resources departments or other economies of scale that lets them screen applicants at a lower marginal cost without introducing complications in the bargaining problem with workers.

Note that firms cannot target their vacancies to a particular group. This implies that if firms hire both types of workers, then

$$q(\theta_t)v = \frac{h_B}{\lambda_{Bz}\frac{u_{Bt}}{u_t}(1-F(x_B^*|p_{Bz}))} = \frac{h_W}{\lambda_{Wz}\frac{u_{Wt}}{u_t}(1-F(x_W^*|p_{Wz}))}. \tag{13}$$

In the baseline model, I assume no differences across groups, with $p_{gz} = p$, $\lambda_{gz} = 1$, and $\chi_{gz} = 0$. In the exogenous callback model, $\lambda_{Bz} < \lambda_{Wz}$. In the statistical discrimination

[14] With a slight abuse of notation, the new-hire wage here is the average wage. Later, I will allow this to depend on workers' idiosyncratic expected productivity.

model, $p_{Bz} < p_{Wz}$. In the taste-based discrimination model, $\chi_{Bz} > \chi_{Wz}$.

Worker's Problem Let $V_t^u(g)$ be value of unemployment for a worker from group g at the end of the period and $V_t^n(n, g, z)$ be the value of a worker employed at a firm of type z that is known to be productive,

$$V_t^n(n, g, z) = w_t^n(n, z, g) + \beta \mathbb{E}_t \left[V_{t+1}^u(g) + (1-\delta)(V_{t+1}^n(n', g, z) - V_{t+1}^u(g)) \right], \tag{14}$$

where n is the number of productive workers. Newly hired workers can be paid different wages and face higher separation rates, captured in the value function,

$$V_t^h(x, n, g, z) = w_t^h(x, n, z, g) + \beta \mathbb{E}_t \left[V_{t+1}^u(g) + x(1-\delta)(V_{t+1}^n(n', g, z) - V_{t+1}^u(g)) \right], \tag{15}$$

where x is the probability the worker is productive, conditional on their signal. For unemployed workers, the value function is

$$\begin{aligned} V_t^u(g) &= b + \beta \mathbb{E}_t V_{t+1}^u(g) \\ &\quad + \underbrace{\beta \mathbb{E}_t \left[\theta_{t+1} q(\theta_{t+1}) \sum_z \lambda_{gz} \frac{\mu_z v_z}{\sum_{\tilde{z}} \mu_{\tilde{z}} v_{\tilde{z}}} \int_{x > x_{gz}^*} \left(V_{t+1}^h(x, n', g, z) - V_{t+1}^u(g) \right) dF(x|p_{gz}) \right]}_{\Omega_t(g)} \end{aligned} \tag{16}$$

where v_z is the equilibrium number of vacancies posted by a firm of type z, μ_z is the (exogenous) mass of type z firms per worker in the economy, and x_{gz}^* is the firm's equilibrium threshold rule.

Wage bargaining Wages are set via Stole & Zwiebel (1996) bargaining in which firms bargain with each worker sequentially and failure to negotiate with a worker requires them to go back and bargain again with the others.[15] Firms and workers split the surplus according

[15] This is a standard bargaining rule in models with endogenous firm size, such as Acemoglu & Hawkins (2014), Baydur (2017), and Elsby & Michaels (2013).

to the following rules

$$\phi D_{t,n_g} = (1-\phi)\left(V_t^n(n', g, z) - V_t^u(g)\right) \tag{17}$$

$$\phi D_{t,x,g} = (1-\phi)\left(V_t^h(x, n', g, z) - V_t^u(g)\right), \tag{18}$$

where ϕ is the worker's bargaining power, D_{t,n_g} is the marginal surplus to the firm of having one more incumbent worker from group g, and $D_{t,x,g}$ is the marginal surplus to the firm of having one more hire from group g with probability x of being productive, both measured after vacancy costs are sunk and hiring thresholds have been chosen. The full details are provided in Online Appendix B.

Using the firm and worker value functions with the sharing rules, we get the following equilibrium wage functions,

$$w^n(n', z, g) = \frac{\alpha\phi}{1-\phi+\alpha\phi} a_t z n'^{\alpha-1} + (1-\phi)(b + \Omega_t(g)) - \phi\chi_{gz} \tag{19}$$

$$w^h(x, n', z, g) = x\frac{\alpha\phi}{1-\phi+\alpha\phi} a_t z n'^{\alpha-1} + (1-\phi)(b + \Omega_t(g)) - \phi\chi_{gz}, \tag{20}$$

where $\Omega_t(g)$ is the value of searching next period for a worker from group g as defined in equation (16). This term is included in addition to the flow value of unemployment, b, because workers who separate are not able to search in the following period.

I assume firms may pay different wages across groups to workers with the same productivity. In the baseline model, worker groups are identical so the wages will be the same. In the taste-based discrimination model, the taste parameter shows up explicitly in equations 19 and 20, lowering the wages paid to Black workers. In all three frameworks with disparities, wage gaps will arise due to differences in the endogenous value of search, $\Omega_t(g)$. Online Appendix B.3 considers an extension that prohibits firms from discriminating on the basis of race in wages.

Aggregation Let μ_z be the mass of type z firms (relative to a unit mass of workers). The mass of unemployed workers in each group evolves according to

$$u_{gt+1} = \pi(g) - \sum_z \mu_z \left(n'_{gz} + h_{gz}(1 - \bar{x}(x^*_{gz}, p_{gz})) \right), \tag{21}$$

where $\pi(g)$ is the share of group g in the population, n'_{gz} is the number of incumbent workers at the start of the next period, and the second term in the sum represents the number of hires who will separate in the next period because they are revealed to be unproductive. These workers are not able to search in the following period and should be excluded from the unemployment rate.

The distribution of employment across firms is given by

$$\Gamma(z) = \frac{\mu_z \sum_g ((1-\delta)n_{gz} + h_{gz})}{\sum_{\tilde{z}} \mu_{\tilde{z}} \sum_g ((1-\delta)n_{g\tilde{z}} + h_{g\tilde{z}})} \tag{22}$$

3.3. Equilibrium

Equilibrium definition Given exogenous masses of firms μ_z, a recursive competitive equilibrium for this economy is a list of functions: (i) value functions for firms, $J_t(n_B, n_W, z)$, (ii) decision rules for vacancies and hiring standards, $v_t(n_B, n_W, z), x^*_{tg}(n_B, n_W, z)$, (iii) value functions for workers $V^n_t(n', g, z)$, $V^h_t(x, n', g, z)$, $V^u_t(g)$, (iv) wage functions $w^n_t(n', g, z)$, $w^h_t(x, n', g, z)$, and (v) worker outside option functions $\Omega_t(g)$; and market tightness θ, a stationary distribution of employment across firms, $\Gamma(z)$, and a stationary distribution of each group of workers in unemployment and each employer type, $\{u_g, n_{gz}\}$.

1. *Firm optimization*: Given θ, $\{u_g, n_{gz}\}$, $\Omega_t(g)$, $w^n_t(n', z, g)$, and $w^h_t(x, n', z, g)$, the set of decision rules $v_t(n_B, n_W, z), x^*_{tg}(n_B, n_W, z)$ solve the firm problem;

2. *Worker optimization*: Given $\theta, \Gamma(z)$, $w^n_t(n', z, g)$, $w^h_t(x, n', z, g)$, and $v_t(n_B, n_W, z), x^*_{tg}(n_B, n_W, z)$, worker value functions $V^n_t(n', g, z)$, $V^h_t(x, n', g, z)$, and $V^u_t(g)$ solve the worker problem and $\Omega_t(g)$ is consistent with value functions;

3. *Wage bargaining*: $w^n_t(n', z, g)$, $w^h_t(x, n', z, g)$ solve the bargaining problem;

4. *Consistency*: The stationary distribution of employment $\Gamma(z)$ is consistent with firm optimization;

5. *Market clearing*: The labor market clears and the distribution of workers across unemployment and employer types, $\{u_g, n_{gz}\}$, is consistent with firm optimization.

Firm's problem solution With the wage equations, the firm's problem can be rewritten as choosing the number of productive workers from each group, subject to a cost minimization problem,

$$\begin{aligned}
J_t(n_B, n_W, z) = \max_{n'_g \geq (1-\delta)n_g} & -C_t\left(\Delta_B, \Delta_W\right) + \frac{1-\phi}{1-\phi+\alpha\phi} a_t z (n')^\alpha \\
& - \sum_g (1-\delta) n_g \Big((1-\phi)(b + \Omega_t(g) + \chi_{gz})\Big) + \beta \mathbb{E}_t J_{t+1}(n'_B, n'_W, z) \\
& \text{s.t.} \\
& \Delta_g = n'_g - (1-\delta) n_g,
\end{aligned}$$

where

$$\begin{aligned}
C_t(\Delta_B, \Delta_W) = \min_{\{x_g^*\}} & \sum_g \frac{\Delta_g}{\bar{x}(x_g^*, p_{gz})} \left(\frac{c_v(z)}{q(\theta_t)(1 - F(x_g^* | p_{gz}))} + (1-\phi)(b + \Omega_t(g) + \chi_{gz})\right) \quad (23) \\
& \text{s.t. } (13),
\end{aligned}$$

and $C_t(\Delta_B, \Delta_W)$ can be understood as the total cost of hiring $\Delta_B + \Delta_W$ *productive* workers.

For an interior solution, the firm's problem is characterized by two first order conditions. For each group,

$$\begin{aligned}
\frac{\partial C_t(\Delta_B, \Delta_W)}{\partial \Delta_g} & + \beta(1-\delta)\mathbb{E}_t\left[(1-\phi)(b + \Omega_{t+1}(g) + \chi_{gz})\right] \\
& = \frac{\alpha(1-\phi)}{1-\phi+\alpha\phi} a_t z (n')^{\alpha-1} + \beta(1-\delta)\mathbb{E}_t\left[\frac{\partial C_{t+1}(\Delta'_B, \Delta'_W)}{\partial \Delta'_g}\right]. \quad (24)
\end{aligned}$$

This condition shows that the firm will hire workers from group g until the marginal cost (left) is equal to the marginal benefit (right). The marginal cost of hiring a productive worker is the hiring cost plus the expected discounted compensation cost for this worker in the next period. The marginal benefit is the effective marginal product of labor (subtracting the share paid to workers as wages) plus the savings to the firm from hiring $(1-\delta)$ fewer workers in the next period.

Using the first order condition from the cost minimization problem, the marginal hiring cost simplifies to

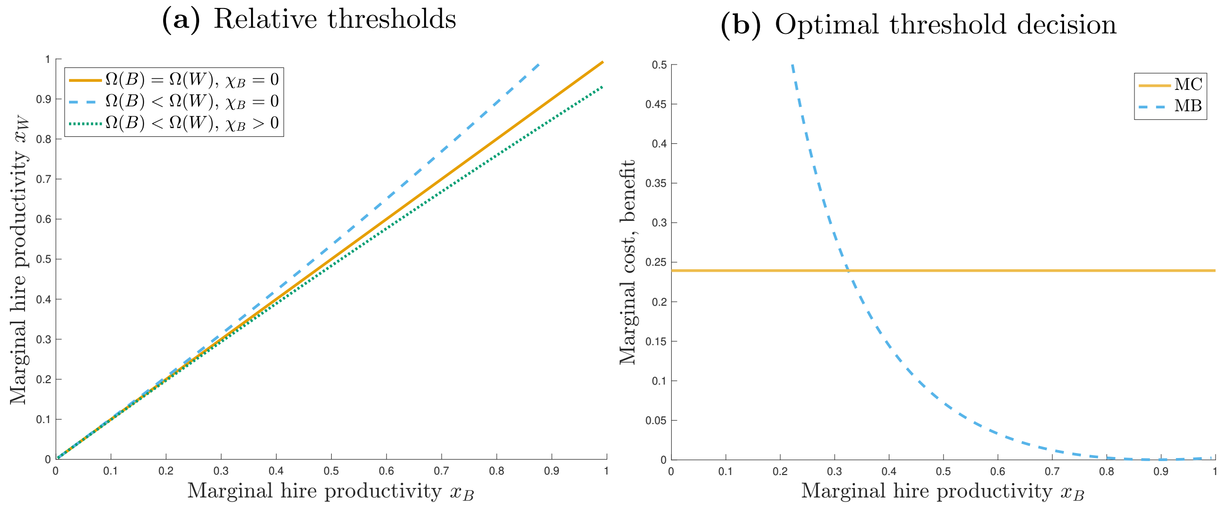
$$\frac{\partial C_t(\Delta_B, \Delta_W)}{\partial \Delta_g} = \frac{(1-\phi)(b+\Omega_t(g)+\chi_{gz})}{x_g^*}, \tag{25}$$

which can be interpreted as the compensation cost for the marginal hire, as the firm needs to hire $\frac{1}{x_g^*}$ workers to hire the last productive worker.

Equations (24) and (25) can be combined to show the relationship between the hiring thresholds for the two groups. Panel (a) of Figure 3 shows this relationship in steady state under various assumptions. First, the orange (solid) line shows that if the outside options of both groups are equal and the taste costs are zero (χ_{gz}=0), then the firm will choose the same marginal hire productivity across groups.[16] If the outside option of the Black population is lower $\Omega(B) < \Omega(W)$ but taste costs are still zero, as shown by the blue (dashed) line, the firm is willing to choose a lower productivity threshold for Black hires because they can compensate them less. Notice that this relationship between x_B^* and x_W^* is determined by market conditions and all firms in the economy face the same tradeoff between marginal hire productivities. However, firms may choose to locate at different points on the frontier, depending on the solution to the cost minimization problem. This is a feature of the exogenous callback gap and statistical discrimination models. In the taste-based model, χ_{gz} acts as a shifter added to $\Omega_t(g)$ that captures the firm's taste or distaste for workers from group g. In that case, this relationship is not the same across firms and the taste costs may outweigh the relative wage effects, leading firms to choose a slightly higher productivity threshold for Black workers, as shown in the green (dotted) line.

[16] This is the condition in Morgan & Várdy (2009), which assumes a fixed wage.

Figure 3: Marginal hire productivity between groups



Panel (a) shows the relationship between hiring thresholds for Black and white workers in steady state, as derived from equations (24) and (25) under various assumptions. Panel (b) shows the firm's optimal threshold choice as defined by equation 26.

Given the relative number of workers a firm wants to hire from each group, the cost minimization solution is given by

$$\frac{c_v(z)}{q(\theta_t)} = \sum_g \lambda_{gz} \frac{u_{gt}}{u_t}(1-\phi)(b + \Omega_t(g) + \chi_{gz}) \frac{\left(\bar{x}(x_g^*, p_{gz}) - x_g^*\right)}{x_g^*}(1 - F(x_g^*|p_{gz})). \tag{26}$$

The left side of equation (26) is the marginal vacancy cost, which is constant due to the linear vacancy technology. The right side of equation (26) is the marginal benefit of posting an additional vacancy, which can be thought of as the marginal cost of compensation. If the firm posts an extra vacancy, it can maintain the same level of hiring by being more selective about the workers it hires, thus reducing the compensation paid to unproductive workers. In the limit, if firms hire only the workers with the highest expected productivity, this cost will go to zero. As they lower the threshold, they accept more workers who will separate. Thus the compensation cost is decreasing with firm selectivity. The firm's optimal decision is at the intersection of these two curves, shown in Panel (b) of Figure 3.

4. Calibration

I calibrate the model at a monthly frequency. I first fix a set of parameters using moments from the data or external estimates. Then, I choose the remaining parameters to match moments from the data.

4.1. Empirical moments

I use data from the SIPP for the empirical moments in the model using the sample described in Section 2.2. I take the unconditional share of Black workers in the sample as given. The other relevant moments include the employment, job-finding, and separation rates by firm size and race. I start with the average employment rate for all workers in my sample. Then, I use the coefficient on the Black dummy variable in Table 2 Panel (a) and the unconditional share of Black workers in the sample to back out employment rates for Black and white workers.[17] I repeat this process for job-finding and separation rates using the Black shares of employed or nonemployed populations and gap estimates from Tables 3 and 4. I repeat this process for large- and small-firm employment, job-finding and separation rates, except I rescale the gap estimates from each table such that the large- and small-firm coefficients sum to the aggregate. For example, the aggregate racial employment gap in Table 2 is -4.1 percentage point and I define the large-firm gap to be 2.3 percentage point using this methodology.[18]

4.2. Fixed parameters

Table 5 summarizes the values of fixed parameters and their sources. Given the monthly frequency, I set the discount factor β to 0.996 to match a quarterly interest rate of 0.012. I set the production curvature α to 0.677, as is common in the RBC literature.

[17] With the Black share of the population of 13.6% and the aggregate employment rate equal to 82.79%, this gives employment rates of 79.3% and 83.4% for Black and white workers, respectively. The employment gap is 4.1 percentage points as in the first row of Table 2 column (1).

[18] Using the coefficient estimates from the first row of Table 2, $2.32 = \frac{2.65}{2.65-7.31} \times -4.08$.

For the exogenous distribution of match quality, I use the functional form assumption from Baydur (2017),

$$F(y) = (y)^{1/(\gamma-1)},$$

with $\gamma > 1$ and $y \in [0,1]$. This distribution is convenient because it is governed by a single parameter. The unconditional mean of match quality is $1/\gamma$. Higher values of γ will imply that screening is more valuable because the ex-ante quality of the pool is lower. I set $\gamma = 3$, following their calibration.

I choose a normalization for signal quality in the baseline model of $p = 0.99$. I use the same normalization across large and small firms because I allow vacancy costs to vary by firm size and I cannot separately identify these parameters. In the statistical discrimination model, what matters is the gap in signal qualities between workers across groups within the same firm.

I set the share of large firms to 0.02 to match the share of firms with 100 or more employees, excluding firms with zero employment, from 1997 Census data, as reported by Axtell (2001). This is the same threshold for defining large firms that I use in the SIPP, and the time period is consistent with my sample that starts in 1996. The aggregate productivity a scales the absolute value of firm size up, and I choose a value of 4.2, which corresponds to small firms having about 30 employees in equilibrium and large firms having 2,800. The Black share of the population is fixed at 0.136 based on the share of Black relative to white population in the SIPP sample described in Section 2.2.

The overall job-finding rate in the SIPP is the matching rate from the perspective of the worker, $\theta q(\theta)$ times the vacancy-weighted average hiring rate across firms and worker groups. I use a standard Cobb-Douglas matching technology, $q(\theta) = \zeta\theta^{-\psi}$, with matching elasticity $\psi = 0.6$, as in Petrongolo & Pissarides (2001). Given a target for market tightness, θ and the fixed parameter value of ζ, this can be expressed as

$$\zeta\theta^{1-\psi}\sum_z\sum_g \frac{v(z)}{v}\frac{u_g}{u}(1 - F(x^*_{gz}|p_{gz})).$$

Thus, given a target of the job-finding rate from the data, ζ governs how selective the firm is. If ζ is low, then the share of matches that are hired increases, whereas if ζ is high, this share decreases. I select ζ such that the weighted average of the hired share of matches is 20%, which is consistent with firms interviewing around five applicants before making an offer, as in Barron *et al.* (1997) or Villena-Roldan (2012).

Table 5: Fixed Parameters

Parameter	Meaning	Value	Source
β	Discount factor	0.996	Quarterly interest rate 0.012
α	Production curvature	0.677	RBC literature
γ	Match quality shape	3	Baydur (2017)
p	Signal quality	0.99	Normalization
υ	Share of large firms	0.02	Axtell (2001)
a	Aggregate productivity	4.2	Relative sizes
π	Black share population	0.136	SIPP
ψ	Matching elasticity	0.6	Petrongolo & Pissarides (2001)
ζ	Matching scale	0.640	Avg. hired share 0.2

4.3. Fitted parameters

The remaining nine parameters are chosen in two parts. For the first three, I use moments from other papers to solve for parameters that affect scaling of the model, given the other parameter values. For the next six, I estimate them using generalized method of moments (GMM), allowing the scale parameters to update with each iteration.

The parameter values are reported in Table 6. I target a market tightness of 0.72 as in Elsby & Michaels (2013) by solving for the mass of firms per worker, μ, consistent with this value. Following the strategy of Baydur (2017), I normalize b such that the equilibrium value of nonemployment for white workers ($b + \Omega(W)$) is equal to 1. I solve for the value of ϕ such that the ratio of b to average productivity (Y/N) is 0.73.

The remaining six parameters affect all of the moments but I will discuss the identification intuition. The exogenous separation rate δ is identified by the average separation rate. The vacancy costs by firm size are identified by the job-finding rates by firm size. To see this, return to the firm's selectivity decision in Panel (b) of Figure 3. An increase in the vacancy cost shifts the marginal cost of vacancies up (blue line), which leads the firm to be less selective, or hire more of its matches, holding fixed the number of hires. This corresponds to a decrease in the number of vacancies the firm needs to post to attract that number of matches. These two effects together map to the job-finding rate at each firm. The relative productivity of large firms, $\frac{z_L}{z_S}$ is identified by the employment share at large firms. If the model had no heterogeneity other than differences in firm productivity, large firms would make the same decisions as small firms but with more workers, because z_L would lead them to hire until their marginal product of labor was the same.

Table 6: Fitted Parameters

Parameter	Meaning	Baseline	Callback gap	Statistical	Taste
Scale parameters					
μ	Number firms/worker	0.009	0.009	0.009	0.009
b	Flow value unemp	0.981	0.981	0.985	0.977
ϕ	Bargaining power	0.351	0.352	0.332	0.370
Estimated parameters					
δ	Exog. separation	0.024	0.024	0.024	0.024
$c_v(L)$	Vacancy cost	0.013	0.013	0.013	0.013
$c_v(S)$	Vacancy cost	0.186	0.187	0.133	0.184
$\frac{z_L}{z_S}$	Relative productivity	4.081	4.080	4.118	4.058
Worker disparity parameters					
λ_{abs}	Match gap	1	0.736	1	1
λ_{rel}	Match bias, large	1	1.016	1	1
Δp_L	Signal gap, large	0	0	0.315	0
Δp_S	Signal gap, small	0	0	0.798	0
$\Delta \chi_L$	Taste penalty, large	0	0	0	0.018
$\Delta \chi_S$	Taste penalty, small	0	0	0	0.057

In the baseline calibration, I only estimate the four parameters described above. The final two parameters govern the disparities between racial groups and vary across the callback gap, statistical discrimination, and taste-based discrimination models. In each version, the moments for identification are the Black-white employment gap and the gap in the large-firm share of employment, essentially the two patterns illustrated in Figure 1. The employment gap governs the overall disparity between Black and white workers in callback rates, signal quality, or taste penalty. The relative large-firm share of employment governs the relative disparity between large and small firms for Black workers.

In the callback gap model, Black workers receive fewer matches than white workers, with λ_{gz} acting as a shifter, such that a vacancy posted by a type z firm matches with a group g worker with probability $\lambda_{gz}\frac{u_{gt}}{u_t}q(\theta_t)$. To match the observed employment gap, Black workers will face a lower rate of matches, $\lambda_{Bz} < 1 < \lambda_{Wz}$. If large and small firms had the same hiring policies, then we would need to see $\lambda_{BL} > \lambda_{BS}$ to match the sorting pattern. I define λ_{abs} and λ_{rel} to govern the absolute and relative patterns, respectively. I define

$$\lambda_{BL} \equiv \lambda_{abs}\lambda_{rel},$$

and λ_{BS} such that

$$\lambda_{abs}\theta q(\theta) = \sum_z \lambda_{Bz}\frac{v(z)}{v}\theta q(\theta),$$

where λ_{abs} captures the aggregate disadvantage in hiring for Black workers and λ_{rel} captures the bias towards large firms. I back out the shifters for white workers, λ_{Wz}, such that firms receive the same number of matches as the baseline case but with a different composition,

$$q(\theta) = \sum_g \lambda_{gz}\frac{u_g}{u}q(\theta).$$

The average match rate for white workers is 43% higher than for Black workers. This magnitude is larger than the 36% average contact gap in the correspondence study literature, as surveyed by Quillian *et al.* (2017). The average reflects a gap of 40% at large firms, which is much larger than the 9% contact gap at very large employers by Kline *et al.* (2022), though the model is calibrated with an average large firm of 100 or more employees, whereas Kline *et al.* (2022) focus on a much higher tail.

In the statistical discrimination model, I normalize the signal quality for white workers to be $p_{Wz} = p = 0.99$ as in the baseline case, which leaves the gap in signal quality at large and small firms as the two remaining parameters, with $p_{Bz} = p_{Wz} - \Delta p_z$. Ignoring firm heterogeneity and holding fixed the Black share of nonemployment, workers' outside options, and market tightness, an increase in the signal quality gap will make firms slightly more lenient in their hiring, as the information is not as informative. The larger effect is that as the signal gap increases, there is a smaller mass of Black workers with a signal above the chosen threshold, and the average productivity conditional on being above that threshold also decreases.[19] The result is that the share of Black workers who are hired and retained in the next period drops, and representation of Black workers falls. Intuitively, the relative large-firm shares of employment govern the degree to which this signal-quality disparity is skewed towards small firms. One way to interpret the parameter values is the relative weight firms place on individual resumes versus the average resume for Black relative to white workers. The parameter estimates for Δp_L and Δp_S, reported in Table 6, imply that large and small firms place 32% and 80% less weight on the individual resumes of Black workers than they do white workers, respectively.

Finally, in the taste-based discrimination model I normalize the taste shifters for white workers to be $\chi_{Wz} = 0$, which leaves the relative taste penalty for Black workers at large and small firms as the two remaining parameters, with $\chi_{Bz} = \chi_{Wz} - \Delta\chi_z$. As these gaps increase, Black workers will be less likely to be hired and retained, leading to a wider employment gap. The relative penalty at large firms is smaller to match the sorting of Black workers to large firms. Quantitatively, the parameter estimates for $\Delta\chi_L$ and $\Delta\chi_S$ in Table 6 represent 1.8% and 5.6% of the average wage at large and small firms, respectively. In the aggregate, this amounts to 0.2% and 0.6% of the total wage bill at large and small firms.

The parameter values governing the frictions are quite large, especially for the statistical and taste-based discrimination models. This is because the only explanation in these models for the -4.1 percentage point gap in employment is the assumed form of discrimination. Online Appendix B.2 shows how the estimates change with the targeted employment gap.

[19] To see this, consider the case where the white worker has signal quality 1. The productivity of the hired white workers will then range from x_W to 1, whereas the productivity of hired Black workers will range from $x_B < x_W$ to $1 - \Delta_p(1 - \mathbb{E}[x])$, which is decreasing in Δ_p.

4.4. Model fit

Table 7: Moments

(a) Targeted

Moment	Data/Model
Separation rate	3.17
Employment share	
Large	64.25
Job-finding rate	
Large	6.45
Small	4.78
Gaps (B-W)	
Employment rate	-4.08
Large-firm employment share	6.20

(b) Untargeted

Moment	Data	Baseline	Callback gap	Statistical	Taste
Separation rate					
Large	3.05	2.83	2.83	2.83	2.83
Small	4.07	3.77	3.77	3.77	3.77
Job-finding gap (B-W)					
Large	0.10	0.00	-0.60	0.58	-0.95
Small	-2.23	0.00	-1.66	0.41	-2.42
Separation gap (B-W)					
Large	0.40	0.00	0.11	0.68	-0.06
Small	0.51	0.00	0.05	2.27	-0.76

The units are percentage points. Panel (a) reports the moments that were targeted in the model calibration, which match the data exactly. Panel (b) reports untargeted moments in the model and the data. The data moments are all calculated in the SIPP.

The model fits the targeted moments exactly, with values shown in Panel (a) of Table 7. Panel (b) shows the fit for untargeted moments. I match the average separation rate by construction, but the model matches the distribution across firm size reasonably well and is consistent across the different assumptions. I target the Black share of employment by firm size but not the gaps in job-finding and separations that contribute to them. The fit of these moments varies widely across the alternative assumptions. The callback gap model slightly overestimate the job-finding gap for Black workers, but capture the importance of small firms, while finding a negative contribution for large firms that is not present in the data. The endogenous racial wage gap leads firms to have slightly lower standards for hiring Black workers, which gives the positive separation gaps through more unsuccessful hires. The statistical model has positive job-finding gaps and overestimates the separation gaps at both types of firms. This is because the firms are also setting a relatively lower standard for hiring Black workers, leading to more job-finding but also higher separations. Finally, in the taste-based model, there are large negative job-finding gaps at both types of firms but also negative separation gaps. This happens due to the opposite effect as the first two models—since hiring Black workers incurs additional taste costs, firms are relatively more selective about these workers, leading to lower job finding but higher retention rates conditional on being hired since the quality of the marginal Black worker is higher.

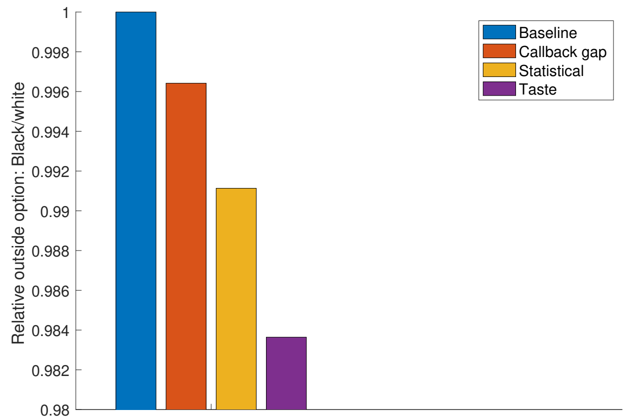
4.5. Model mechanisms across calibrations

Figure 4 illustrates how equilibrium hiring patterns by race and firm size vary across the four calibrations. The blue bar shows the baseline case in which there are no differences by race. Relative outside options are the same, $\frac{b+\Omega(B)}{b+\Omega(W)} = 1$. The probability that the marginal hire is productive, x^*_{gz}, is higher for large firms because they have a lower vacancy cost, making it less costly for them to be selective. The share hired, $1 - F(x^*_{gz}|p)$, is therefore smaller for large firms.

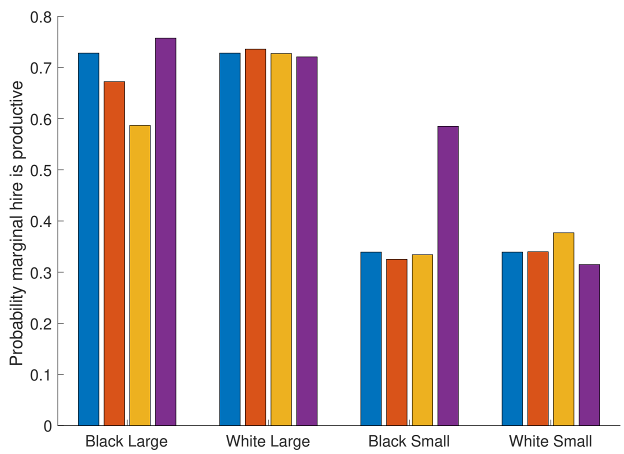
As disparities are introduced, equilibrium outside options become worse for Black workers. In the callback gap model, this leads firms to be slightly less selective about the marginal Black hire relative to the baseline case, because they can bargain lower wages with Black workers. Conditional on matching, Black workers therefore have a slightly higher likelihood of being hired, whereas white workers have a very slightly smaller likelihood relative to the baseline case. In the statistical discrimination model, the gap in outside options similarly makes firms more even more lenient in their hiring standards for Black workers. However, due to the increased noise in the signal for Black workers, the share hired is slightly lower than the callback gap model because there are fewer workers who meet the criteria. In the taste-based model, this incentive to be more lenient about hiring Black workers because of relative wages is still present, but it is outweighed by the direct taste cost, which makes

Figure 4: Comparison of calibrations

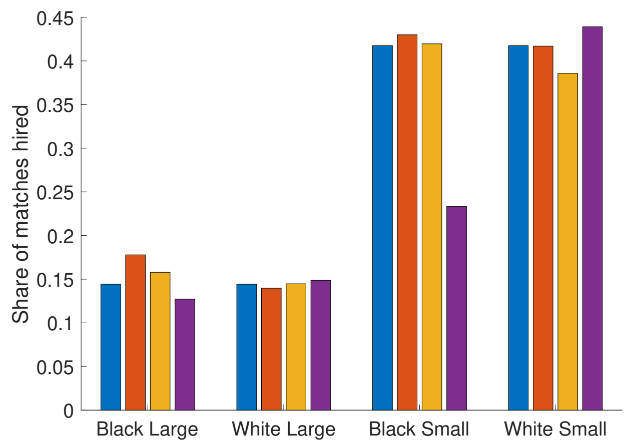
(a) Relative outside options



(b) Selectivity



(c) Share hired



firms set relatively higher standards for hiring Black workers overall. This is especially true at small firms, where the taste shifters are higher.

5. Counterfactuals

5.1. Permanent decrease in aggregate productivity

I use the quantitative model to consider a permanent, unanticipated negative shock to aggregate productivity, a, and compare steady states before and after. Given that the Great Recession is a major source of the variation in my data, this type of shock is relevant. I choose the scale of the decrease such that the total drop in employment for white workers in the baseline model matches the empirical average decrease when the unemployment rate is 1-standard-deviation higher, as reported in Table 2.[20]

Table 8 reports the results of this exercise across the four calibrations. By construction, the data and model match exactly in the first row for the total change in employment for white workers in the baseline model. Moving to the alternative calibrations, white workers are slightly less affected by the lower productivity, except in the statistical discrimination model. The next two rows compare the decreases in employment at each type of firm between the data and the model, with the numbers from the data taken from Table 2 Panel (b) and rescaled to include only large and small firms. The model is relatively consistent with the data in terms of the shares attributed to each type of firm, though the decrease in employment is less skewed towards large firms than it is in the data. These shares are also relatively consistent across the alternative calibrations.

Table 8: Steady state comparison

Changes: low - high productivity	Data	Baseline	Callback gap	Statistical	Taste
White employment rate	-1.49	-1.49	-1.44	-1.50	-1.27
Large	-1.21	-1.09	-1.03	-1.18	-0.96
Small	-0.28	-0.40	-0.41	-0.32	-0.31
Employment gap	-0.64	0.00	-0.29	-1.26	-1.78
Large	-1.14	0.00	-0.37	0.12	-0.98
Small	0.50	0.00	0.08	-1.38	-0.80

This table shows the comparison between the low productivity relative to high productivity steady state. The units are percentage points. The low productivity is 0.01 log points below high productivity, chosen such that the difference in the white employment rate in the first row matches between data and baseline model. The data counterparts are taken from the regression results in columns (1) and (2) of Table 2 Panel (b), rescaled to include only large and small firms.

The second group of Table 8 shows the difference in the racial employment gap between steady states. The baseline model has no change, as there is no difference between Black and white workers in this model. Across the other three models, the employment gap worsens in the low productivity steady state, though the magnitudes vary and the contributions of large and small firms differ. The callback gap model explains about 45% of the employment

[20]This results in a 0.01 log point decrease in productivity.

gap change in the data, while capturing that the employment gap worsens by more at large firms and improves slightly at small firms. In the statistical and taste-based discrimination models, the employment gap worsens by more than the change in the data. In the statistical discrimination model, the worse employment gap is entirely driven by small firms. In the taste-based discrimination model, large firms contribute slightly less than their 64% employment share to the change in the gap.

5.2. Discussion

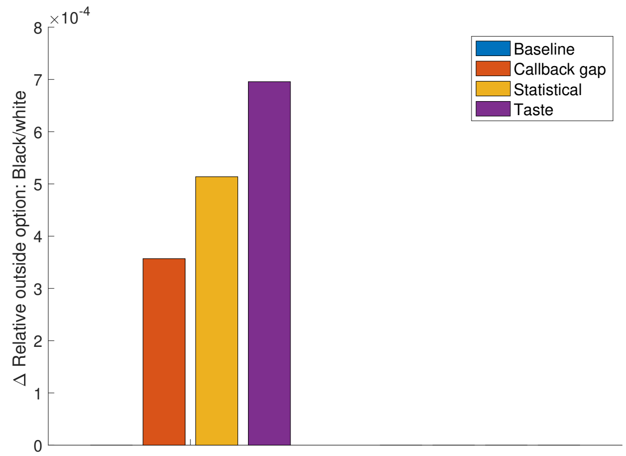
In the low productivity steady state, the racial employment gap worsens across all three calibrations with racial disparities. To understand why this happens, it is helpful to return to the comparison of relative outside options, selectivity, and hiring shares across the different calibrations. Figure 5 shows the change in these moments relative to the high productivity steady state shown in Figure 4.

In the baseline model, there is no change in relative outside options, again, because there are no differences by race. With lower productivity, firms want to hire less overall, which leads market tightness to decrease. The decrease in market tightness causes a decrease in the marginal cost of vacancy posting, which determines the optimal selectivity threshold in Equation 26. Lower cost of posting vacancies makes it less costly to be selective about which workers to hire, leading the productivity of the marginal hire to increase and the share hired to decrease. This effect is stronger at small firms because the vacancy cost is higher so a change in market tightness makes them adjust the hiring threshold more than large firms.

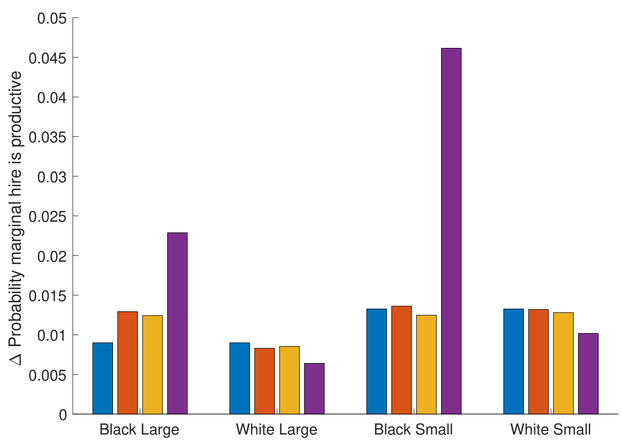
Moving to the racial disparity calibrations, relative outside options improve marginally relative to the high productivity steady state, although outside options worsen for everyone in absolute terms. This narrowing of relative outside options leads firms to become relatively more selective about hiring Black workers, since they can no longer bargain much lower wages with them. This effect is generally bigger at large firms because they face smaller frictions, and therefore the benefits of hiring Black workers at low wages in the high productivity steady state relative to the costs are greater than for small firms. When these benefits shrink in the low productivity steady state, it makes large firms adjust more. This is especially apparent

Figure 5: Comparison of steady states across calibrations

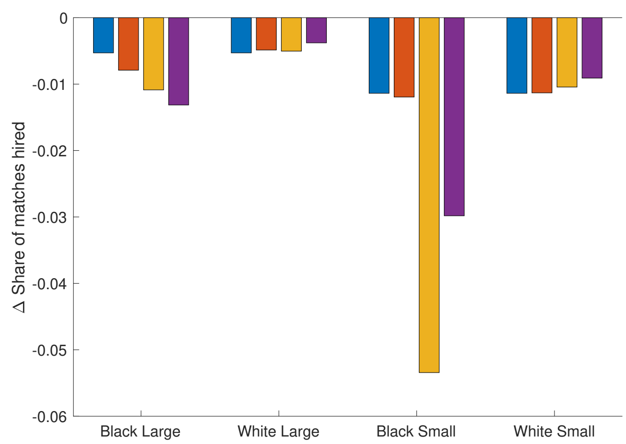
(a) Relative outside options



(b) Selectivity



(c) Share hired



in the callback gap model, where conditional on matching, there are no differences between Black and white workers besides their outside options in the bargaining process. Thus, the result in Table 8 that the employment gap worsens more at large firms in the callback gap model is primarily driven by the narrowing of outside options that reduce firms' incentives to hire Black workers. In the statistical and taste-based discrimination models, these effects are still bigger at large firms, but the direct effects of the hiring frictions are stronger, making small firms more important for the total change.

5.3. Sensitivity of results to model assumptions

The counterfactual exercise shows that in a slack labor market, job-finding worsens more for Black workers. Some of this effect is driven by firms becoming more selective, and much of it is due to changes in equilibrium wages, which vary by race. Table 9 reports the comparison of steady states in a version of the model in which firms are constrained to pay the same wage. Model details are described in Online Appendix B.3. Without wage discrimination, workers still have endogenous differences in outside options, due to differences in job-finding and hiring rates, but I assume firms do not know who they are bargaining with. This leads them to bargain wth the average worker. Thus, if Black workers have lower outside options, firms that employ more Black workers will have a lower wage bill, but Black and white workers at those firms are paid the same wage. The incentives for firms are therefore the same, but in equilibrium the relative outside options are more similar, relative to the results in Figure 4 Panel (a).

Table 9: Steady state comparison, no wage discrimination

Changes: low - high productivity					
	Data	Baseline	Callback gap	Statistical	Taste
White employment rate	-1.49	-1.49	-1.46	-1.53	-1.39
Large	-1.21	-1.09	-1.05	-1.16	-1.17
Small	-0.28	-0.40	-0.40	-0.38	-0.22
Employment gap	-0.64	0.00	-0.22	-0.64	-0.62
Large	-1.14	0.00	-0.24	0.08	0.70
Small	0.50	0.00	0.02	-0.72	-1.32

This table shows the comparison between the low productivity and high productivity steady states in the model in which firms are constrained to pay the same wage. The units are percentage points. The low productivity is 0.01 log points below high productivity, chosen such that the difference in the white employment rate in the first row matches between data and baseline model. The data counterparts are taken from the regression results in columns (1) and (2) of Table 2 Panel (b), rescaled to include only large and small firms.

The models without wage discrimination have more moderate decreases in the employment gap, shown in Table 9, relative to the results with wage discrimination reported in Table 8. In the callback gap model, the difference is most similar to the case with wage discrimination, because there are no other frictions preventing firms from hiring Black workers once they are at the match stage. In this model, the employment gap still worsens at large firms and marginally improves at small firms.

In the models with discrimination, the worsening of the employment gap is driven by small firms. This is because the direct effects of the frictions are relatively more important than the relative wage effects, and small firms have more severe frictions for hiring Black workers.

Overall, the exact assumption about the reason for racial disparities in employment and sorting between large and small firms is important for understanding the responsiveness of employment gaps to changes in productivity. In the most general case, with exogenous callback gaps, wage discrimination plays a minor role and large firms are more responsive to productivity in their treatment of Black workers. In the more specific cases of either statistical or taste-based discrimination, the wage margin is important for the relative contributions of large and small firms.

Online Appendix B.2 presents additional sensitivity to the size of racial employment and sorting gaps targeted in the calibration.

6. Conclusion

This paper starts by shedding light on the interactions between firm types and the Black-white employment gap over the business cycle. In the aggregate data, large firms contribute an additional 5-6% to the excess volatility of Black employment relative to white employment. Turning to micro-data, within individuals, employment at large firms is more responsive to the state unemployment rate for Black workers relative to white workers. This pattern is apparent in hiring as well.

I showed that a flexible model of racial disparities in the hiring process can generate both the sorting of Black workers towards large firms and the disproportionate responsiveness of Black employment to aggregate productivity changes. Across three alternative assumptions about the source of racial disparities in hiring, I find that a permanent decrease in productivity leads to a steady state with a wider racial employment gap. In each case, a more slack labor market leads firms to be more selective about hiring, which disproportionately affects Black workers, and relative wages adjust, amplifying the effects for large firms especially.

The relative adjustments of large and small firms depend on the source of racial hiring disparities. Large firms are the primary drivers of the worsening employment gap in the model in which racial disparities arise due to different rates of matching between Black and white workers. This type of friction could arise due to bias in applicant screening processes or personal connections affecting the chances of getting an interview. Large firms contribute relatively less in the models in which racial disparities arise due to statistical or taste-based discrimination. In reality, the racial employment gap and sorting across firms likely reflect several factors.

Understanding how these results differ across alternative assumptions is importing for policymakers thinking about how to improve labor market equality. First, regulations that seek to limit discrimination by focusing on large firms may miss some of the economy-wide effects of discrimination among smaller players. Second, while a tighter labor market can improve employment outcomes for marginalized groups more, the full gains of the tight economy are not felt equally, with potential differences in the pass-through of wages.

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Online Appendix

A. Empirical Appendix

A.1. SIPP data description

Data definitions My sample includes about 215,000 individuals, whom I observe for an average of 28 months. Table A.1 reports summary statistics.

Table A.1: Summary statistics

	Black		White	
	Mean	SD	Mean	SD
Demographics				
Age (years)	39.8	12.9	42.8	13.7
Women	55.1	49.7	48.5	50.0
Married	38.6	48.7	62.3	48.5
College	17.7	38.2	31.7	46.5
Metro area	86.6	34.1	76.3	42.5
State unemployment	6.0	2.1	5.8	2.1
Employed				
Any	75.9	42.8	83.9	36.8
Large	39.5	48.9	37.3	48.4
Small	14.9	35.6	21.9	41.3
Government	16.3	37.0	13.2	33.9
Self-employment	4.6	20.8	10.5	30.6
Hires				
Any	3.1	17.2	2.7	16.1
Large	1.9	13.5	1.3	11.4
Small	0.9	9.4	1.0	10.1
Separations				
Any	2.9	16.7	2.6	15.9
Large	1.7	12.8	1.2	11.1
Small	0.8	8.9	1.0	9.8

The table reports means and standard deviations from the SIPP. The units are percentage points unless otherwise specified.

I define occupations at the two-digit level. The occupation classification system changes between the 2001 and 2004 panels. Rather than impose an imperfect mapping, I define a set of 17 categories for the first half of the sample and a set of 22 categories for the second. For the 1996 and 2001 panels the categories are: executive, administrative, and managerial; managment-related; professional specialty; technicians and related; sales; administrative support; housekeeping and cleaning; protective service; farm operations and managers; other agriculture; mechanics and repairers; construction trades; extractive occupations; precision production; machine operators; transportation. For the 2004 and 2008 panels the categories are: management; business and financial; computer and math; engineering; science; social work; legal; education; artists, entertainment, and media; health; health support; law enforcement; food service; maintenance; services; retail; administrative and postal; agriculture; extraction and trades; maintenance and installation; production; transportation.

I define industries at the two-digit level: (11) agriculture, (21) forestry, fishing and hunting; mining, quarrying, and oil and gas extraction; (22) utilities; (23) construction; (31-33) manufacturing; (42) wholesale trade; (44-45) retail trade; (48-49) transportation and warehousing; (51) information; (52-53) finance, insurance, and real estate; (55-56) management, administrative support, and waste management services; (61) educational services; (62) health care and social assistance; (71) arts, entertainment, and recreation; (72) accommodation and food services; (81) other services; (92) public administration.

I define education in four bins: less than high school degree, high school degree or equivalent, some college, and college degree.

I construct a measure of firm size using three survey questions: "About how many persons are employed by ...'s employer at the location where ... works?" (tempsiz), "Does ...'s employer operate in more than one location?" (eemploc), and "About how many persons were employed by ...'s employer at ALL LOCATIONS together" (tempall). I choose 100 employees as the cutoff for large firms because it is available across waves even though the bins change over time. For all panels before 2008, there were three bins for both establishment and firm size with the largest being 100 or more. These bins were used in the 2008 panel as well until the 11th wave, when the bins were expanded to include eight bins for establishment size (three with 100 or fewer) and six bins for firm size (two with 100 or fewer). The number of individuals reporting working for the same employer but at a different size increases substantially in the 11th wave and remains elevated for the rest of the sample. For this reason, I exclude the final six waves of the panel.

A.2. Alternative specification

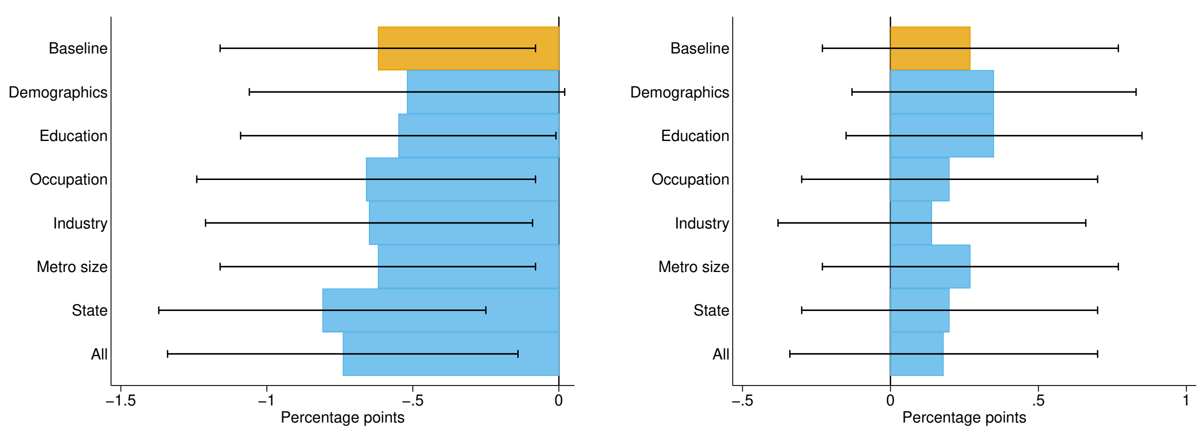
In this section, I modify the primary regression specification to include interactions between worker characteristics and the state unemployment rate in addition to the Black dummy variable interaction,

$$E_{ijt} = \alpha_{ij} + \beta_j \mathrm{UR}_t + \beta_j^B \mathrm{Black} \times \mathrm{UR}_t + \Gamma X_{it} \times \mathrm{UR}_t + \epsilon_{ijt}. \tag{A.1}$$

This allows for the possibility that the change in the employment rate for Black workers is more responsive due to differences in industry, education, or other characteristics. Figure A.1 reports the coefficient estimates with different control variables interacted. The estimates are relatively stable across the different specifications.

Figure A.1: Regression estimates with additional control interaction terms

(a) Large firms β_L^B **(b)** Small firms β_S^B



The figure reports the coefficient estimates for the interaction between the Black dummy variable and the state unemployment rate from equation A.1 with varying controls X_{ijt}. Demographics includes age and age-squared, both standardized, and marital status interacted with gender.

A.3. Results by gender

This section reports the main empirical results by gender. Tables A.2 and A.3 show the results from Table 2 by gender. The results for men are weaker than the results for women, and the individual fixed effects are more important.

Table A.2: Employment fluctuations by firm type, men

(a) Individual controls

	(1) All	(2) Large	(3) Small	(4) Government	(5) Self
Black	-5.29	1.45	-6.61	2.16	-2.36
	(0.32)	(0.46)	(0.37)	(0.31)	(0.28)
UR	-1.75	-0.85	-0.82	0.09	-0.19
	(0.14)	(0.17)	(0.16)	(0.10)	(0.13)
Black × UR	-0.43	-0.12	0.03	-0.67	0.35
	(0.32)	(0.42)	(0.32)	(0.27)	(0.25)
R2	0.082	0.185	0.068	0.408	0.142
N	2,964,624	2,964,624	2,964,624	2,964,624	2,964,624
Black mean	76.70	39.45	15.74	14.60	6.17
White mean	86.90	38.83	22.23	11.53	13.43

(b) Individual fixed effects

	(1) All	(2) Large	(3) Small	(4) Government	(5) Self
UR	-1.63	-1.41	-0.34	0.12	-0.06
	(0.30)	(0.18)	(0.14)	(0.08)	(0.09)
Black × UR	-0.57	-0.65	0.21	-0.54	0.45
	(0.38)	(0.41)	(0.35)	(0.22)	(0.21)
R2	0.563	0.749	0.686	0.868	0.847
N	3,019,437	3,019,437	3,019,437	3,019,437	3,019,437
Black mean	76.70	39.45	15.74	14.60	6.17
White mean	86.90	38.83	22.23	11.53	13.43

The table reports differences in employment probability by race and macroeconomic conditions for men. The units are percentage points. UR is the state-level unemployment rate expressed in standard deviations from the mean. Panel (a) includes controls for age; age-squared; marital status interacted with gender; education; state; metro area size; modal industry and occupation. Panel (b) includes individual fixed effects. Standard errors are clustered by person and month.

Table A.3: Employment fluctuations by firm type, women

(a) Individual controls

	(1) All	(2) Large	(3) Small	(4) Government	(5) Self
Black	-2.88	3.56	-7.46	3.11	-1.86
	(0.31)	(0.41)	(0.32)	(0.31)	(0.19)
UR	-0.62	-0.20	-0.13	-0.24	-0.05
	(0.19)	(0.18)	(0.15)	(0.12)	(0.11)
Black × UR	-0.97	-0.81	0.34	-0.73	0.15
	(0.29)	(0.37)	(0.28)	(0.27)	(0.17)
R2	0.056	0.158	0.070	0.375	0.114
N	3,002,944	3,002,944	3,002,944	3,002,944	3,002,944
Black mean	75.20	39.48	14.18	17.72	3.24
White mean	80.67	35.67	21.48	14.98	7.37

(b) Individual fixed effects

	(1) All	(2) Large	(3) Small	(4) Government	(5) Self
UR	-1.35	-1.18	-0.26	-0.07	0.10
	(0.30)	(0.20)	(0.14)	(0.11)	(0.07)
Black × UR	-0.74	-0.62	0.30	-0.15	-0.09
	(0.38)	(0.35)	(0.31)	(0.23)	(0.14)
R2	0.577	0.729	0.676	0.843	0.793
N	3,077,848	3,077,848	3,077,848	3,077,848	3,077,848
Black mean	75.20	39.48	14.18	17.72	3.24
White mean	80.67	35.67	21.48	14.98	7.37

The table reports differences in employment probability by race and macroeconomic conditions for women. The units are percentage points. UR is the state-level unemployment rate expressed in standard deviations from the mean. Panel (a) includes controls for age; age-squared; marital status interacted with gender; education; state; metro area size; modal industry and occupation. Panel (b) includes individual fixed effects. Standard errors are clustered by person and month.

Tables A.4 and A.5 report the results from Table 3 separately by gender. Again, the results are generally stronger for women. For men, the Black-unemployment interaction coefficients become positive for job-finding (though not for hiring). Again, the attenuation is smaller at large firms, indicating that large firms are still relatively more important for the gap in job-finding rates in higher unemployment periods.

Table A.4: Job inflows by firm type, men

(a) Hires (percent of population)

	(1) All	(2) Large	(3) Small	(4) All	(5) Large	(6) Small
Black	0.08	0.28	-0.26			
	(0.06)	(0.04)	(0.03)			
UR	-0.05	-0.06	-0.02	-0.08	-0.12	0.01
	(0.03)	(0.02)	(0.02)	(0.09)	(0.04)	(0.03)
Black × UR	-0.06	-0.04	-0.01	-0.22	-0.15	-0.10
	(0.05)	(0.04)	(0.03)	(0.10)	(0.09)	(0.05)
R2	0.012	0.007	0.007	0.079	0.072	0.072
N	2,964,624	2,964,624	2,964,624	3,019,437	3,019,437	3,019,437
Black mean	3.02	1.75	0.96	3.02	1.75	0.96
White mean	2.54	1.24	1.04	2.54	1.24	1.04
Individual FE				X	X	X

(b) Job-finding

	(1) All	(2) Large	(3) Small	(4) All	(5) Large	(6) Small
Black	-3.25	-0.62	-2.49	-7.82	-2.32	-5.15
	(0.31)	(0.21)	(0.17)	(0.63)	(0.46)	(0.36)
UR	-1.69	-0.91	-0.65	-5.42	-2.91	-2.17
	(0.21)	(0.11)	(0.10)	(0.28)	(0.19)	(0.17)
Black × UR	0.42	0.13	0.28	2.00	0.62	1.31
	(0.25)	(0.19)	(0.13)	(0.46)	(0.36)	(0.25)
R2	0.037	0.027	0.021	0.036	0.028	0.024
N	372,813	372,813	372,813	116,110	116,110	116,110
Black mean	9.88	5.46	3.05	16.09	9.18	5.10
White mean	13.41	6.16	5.26	24.19	11.59	10.02
Unemployed sample				X	X	X

The table reports differences in hiring rates by race and macroeconomic conditions for men. The units are percentage points. UR is the state-level unemployment rate expressed in standard deviations from the mean. Panel (a) includes all individuals and panel (b) restricts to non-employed or unemployed individuals. All columns without fixed effects include controls for age; age-squared; marital status interacted with gender; education; state; metro area size; modal industry and occupation. Standard errors are clustered by person and month.

Table A.5: Job inflows by firm type, women

(a) Hires (percent of population)

	(1) All	(2) Large	(3) Small	(4) All	(5) Large	(6) Small
Black	-0.02	0.34	-0.34			
	(0.05)	(0.04)	(0.03)			
UR	-0.17	-0.10	-0.07	-0.21	-0.18	-0.05
	(0.04)	(0.02)	(0.01)	(0.12)	(0.06)	(0.04)
Black × UR	-0.09	-0.13	0.03	-0.23	-0.14	-0.07
	(0.04)	(0.03)	(0.02)	(0.09)	(0.07)	(0.05)
R2	0.010	0.007	0.005	0.070	0.066	0.064
N	3,002,944	3,002,944	3,002,944	3,077,848	3,077,848	3,077,848
Black mean	3.07	1.93	0.85	3.07	1.93	0.85
White mean	2.77	1.39	1.03	2.77	1.39	1.03
Individual FE				X	X	X

(b) Job-finding

	(1) All	(2) Large	(3) Small	(4) All	(5) Large	(6) Small
Black	-1.28	0.57	-1.62	-8.27	-2.32	-5.02
	(0.22)	(0.16)	(0.12)	(0.53)	(0.45)	(0.32)
UR	-0.75	-0.45	-0.27	-5.16	-2.87	-1.81
	(0.19)	(0.10)	(0.07)	(0.37)	(0.24)	(0.18)
Black × UR	-0.60	-0.58	0.01	1.25	0.01	1.10
	(0.17)	(0.14)	(0.09)	(0.37)	(0.31)	(0.20)
R2	0.019	0.019	0.010	0.040	0.026	0.023
N	533,258	533,258	533,258	107,092	107,092	107,092
Black mean	9.52	5.75	2.59	17.25	10.93	4.60
White mean	10.29	4.85	3.64	25.07	12.86	8.67
Unemployed sample				X	X	X

The table reports differences in hiring rates by race and macroeconomic conditions for women. The units are percentage points. UR is the state-level unemployment rate expressed in standard deviations from the mean. Panel (a) includes all individuals and panel (b) restricts to non-employed or unemployed individuals. All columns without fixed effects include controls for age; age-squared; marital status interacted with gender; education; state; metro area size; modal industry and occupation. Standard errors are clustered by person and month.

Tables A.6 and A.7 report the results of Table 4 by gender. For men, we see a small worsening of the racial separation gap for separations with higher unemployment, consistent with previous literature that focused on men, such as Couch & Fairlie (2010). The point estimates are not statistically significant. We see the opposite pattern for women, which is driving the overall pattern seen in Table 4.

Table A.6: Separation rates by firm type, men

	(1) All	(2) Large	(3) Small	(4) All	(5) Large	(6) Small
Black	0.38	0.46	0.63	0.38	0.49	0.58
	(0.07)	(0.09)	(0.17)	(0.05)	(0.06)	(0.12)
UR	0.05	0.00	0.17	0.21	0.21	0.41
	(0.04)	(0.04)	(0.07)	(0.03)	(0.03)	(0.05)
Black × UR	0.06	0.04	0.01	0.07	0.08	0.01
	(0.07)	(0.09)	(0.16)	(0.05)	(0.07)	(0.12)
R2	0.013	0.013	0.011	0.007	0.007	0.007
N	2,471,350	1,171,446	654,400	2,588,226	1,171,446	654,400
Black mean	6.78	6.69	11.06	3.46	3.11	5.67
White mean	2.93	2.80	4.06	1.30	1.25	2.03
Involuntary				X	X	X

The table reports differences in separation rates by race and macroeconomic conditions for men. The units are percentage points. Columns (1)-(3) include all separations and columns (4)-(6) restrict the outcome variable to involuntary separations. UR is the state-level unemployment rate expressed in standard deviations from the mean. All columns include controls for age; age-squared; marital status interacted with gender; education; state; metro area size; modal industry and occupation. Standard errors are clustered by person and month.

Table A.7: Separation rates by firm type, women

	(1) All	(2) Large	(3) Small	(4) All	(5) Large	(6) Small
Black	0.14	0.32	0.30	0.32	0.40	0.44
	(0.06)	(0.08)	(0.14)	(0.04)	(0.05)	(0.09)
UR	-0.11	-0.12	-0.18	0.14	0.14	0.17
	(0.05)	(0.05)	(0.06)	(0.03)	(0.03)	(0.03)
Black × UR	-0.06	-0.18	0.10	-0.07	-0.06	-0.07
	(0.05)	(0.07)	(0.13)	(0.03)	(0.05)	(0.08)
R2	0.012	0.012	0.011	0.004	0.005	0.005
N	2,355,302	1,119,732	629,286	2,462,015	1,119,732	629,286
Black mean	6.47	6.64	10.14	2.74	2.62	3.93
White mean	3.44	3.33	4.11	1.24	1.22	1.53
Involuntary				X	X	X

The table reports differences in separation rates by race and macroeconomic conditions for women. The units are percentage points. Columns (1)-(3) include all separations and columns (4)-(6) restrict the outcome variable to involuntary separations. UR is the state-level unemployment rate expressed in standard deviations from the mean. All columns include controls for age; age-squared; marital status interacted with gender; education; state; metro area size; modal industry and occupation. Standard errors are clustered by person and month.

B. Model Appendix

B.1. Wage setting

Suppose the firm can observe the worker's group (g) and new hire status at the time of bargaining and is allowed to fully discriminate on both dimensions. The firm's value at the time of bargaining is given by

$$\begin{aligned}
D_t(\{\tilde{n}_g\},\{h_g\},\{\bar{x}_g\},z) =& a_t z(n')^\alpha - \sum_g \Big(\tilde{n}_g(w_t^n(n',z,g)+\chi_{gz}) + h_g(w_t^h(x_g,n',z,g)+\chi_{gz})\Big) \\
&+ \beta\mathbb{E}_t J_{t+1}(n'_B,n'_W,z) \\
&\text{s.t.} \\
&n' = \sum_g n'_g \\
&n'_g = \tilde{n}_g + \bar{x}_g h_g
\end{aligned}$$

where $\tilde{n}_g = (1-\delta)n_g$ is the number of non-separated workers from group g from the previous period and $h_g = \lambda_{gz}\frac{u_{gt}}{u_t} v q(\theta_t)(1-F(x_g|p_{gz}))$ is the number of hires from group g with average expected productivity $\bar{x}_g$. The last line shows the mapping back to the law of motion in equation (8).

To relate the firm value at bargaining back to the firm's problem from the main text, notice that vacancies can be rewritten as[21]

$$v = \sum_g \frac{h_g}{q(\theta_t)(1-F(x_g|p_{gz}))}$$

Then using this expression, the firm's problem from equation (6) can be equivalently ex-

[21]The omitted step is
$v = \frac{h_g}{\lambda_{gz}\frac{u_{gt}}{u_t}q(\theta_t)(1-F(x_g|p_{gz}))} = \lambda_{Bz}\frac{u_{Bt}}{u_t}\frac{h_B}{\lambda_{Bz}\frac{u_{Bt}}{u_t}q(\theta_t)(1-F(x_B|p_{Bz}))} + \lambda_{Wz}\frac{u_{Wt}}{u_t}\frac{h_W}{\lambda_{Wz}\frac{u_{Wt}}{u_t}q(\theta_t)(1-F(x_W|p_{Wz}))}$

pressed as

$$J_t(n_B, n_W, z) = \max_{h_B, h_W, x_B, x_W} -\sum_g \frac{c_v(z)h_g}{q(\theta_t)(1 - F(x_g|p_{gz}))} + D_t(\{(1-\delta)n_g\}, \{h_g\}, \{\bar{x}_g(x_g)\}, z)$$

where the first term comes the expression for vacancies from the law of motion for productive hires.

To solve the wage problem, we need the marginal surplus for each group, $D_{t,\tilde{n}_g}$ and D_{t,h_g}, where the arguments of $D()$ are omitted to ease notation.

$$\begin{aligned}
D_{t,\tilde{n}_g} =& \alpha a_t z(n')^{\alpha-1} - w_t^n(n', z, g) - \chi_{gz} - \sum_k \left(\tilde{n}_k w^n_{t,n'}(n', z, k) + h_k w^h_{t,n'}(\bar{x}_k, n', z, k)\right) \\
& + \beta(1-\delta)\mathbb{E}_t D_{t+1,\tilde{n}_g} \\
D_{t,h_g} =& \bar{x}_g \alpha a_t z(n')^{\alpha-1} - w_t^h(x_g, n', z, g) - \chi_{gz} - \bar{x}_g \sum_k \left(\tilde{n}_k w^n_{t,n'}(n', z, k) + h_k w^h_{t,n'}(\bar{x}_k, n', z, k)\right) \\
& + \beta(1-\delta)\bar{x}_g \mathbb{E}_t D_{t+1,\tilde{n}_g}
\end{aligned}$$

The marginal surplus from the worker's side is given by

$$\begin{aligned}
V_t^n(n', g, z) - V_t^u(g) =& w_t^n(n', z, g) - (b + \Omega_t(g)) + \beta(1-\delta)\mathbb{E}_t \left[V^n_{t+1}(n'', g, z) - V^u_{t+1}(g)\right] \\
V_t^h(\bar{x}_g, n', g, z) - V_t^u(g) =& w_t^h(\bar{x}_g, n', z, g) - (b + \Omega_t(g)) + \beta(1-\delta)\bar{x}_g(z)\mathbb{E}_t \left[V^n_{t+1}(n'', g, z) - V^u_{t+1}(g)\right]
\end{aligned}$$

Using the bargaining rules defined in equations (17) and (18),

$$\begin{aligned}
w_t^n(n', z, g) =& \phi \alpha a_t z(n')^{\alpha-1} - \phi \sum_k \left(\tilde{n}_k w^n_{t,n'}(n', z, k) + h_k w^h_{t,n'}(\bar{x}_k, n', z, k)\right) \\
& - \phi \chi_{gz} + (1-\phi)(b + \Omega_t(g)) \\
w_t^h(\bar{x}_g, n', z, g) =& \bar{x}_g \phi \alpha a_t z(n')^{\alpha-1} - \bar{x}_g \phi \sum_k \left(\tilde{n}_k w^n_{t,n'}(n', z, k) + h_k w^h_{t,n'}(\bar{x}_k, n', z, k)\right) \\
& - \phi \chi_{gz} + (1-\phi)(b + \Omega_t(g))
\end{aligned}$$

Notice that the relationship between new hire wages and existing worker wages is given by

$$w_t^h(\bar{x}_g, n', z, g) = \bar{x}_g w_t^n(n', z, g) + (1 - \bar{x}_g)\left[(1-\phi)(b + \Omega_t(g)) - \phi\chi_{gz}\right]$$

which implies

$$w_{t,n'}^h(x_g, n', z, g) = \bar{x}_g w_{t,n'}^n(n', z, g)$$

Next, the wage gap between existing workers from the two groups is given by

$$w_t^n(n', z, B) - w_t^n(n', z, W) = (1-\phi)(\Omega_t(B) - \Omega_t(W)) + \phi\left(\chi_{Wz} - \chi_{Bz}\right)$$

which doesn't depend on the employment at the firm, and so $w_{n'}(n', z, B) = w_{n'}(n', z, W)$. Using these observations, we can simplify the differential equation for $w_t^n(n', z, g)$,

$$w_t^n(n', z, g) = \phi a_t z (n')^{\alpha-1} - \phi n' w_{t,n'}^n(n', z, g) + (1-\phi)(b + \Omega_t(g)) - \phi\chi_{gz}$$

Solving this differential equation gives the following equilibrium wages

$$\begin{aligned}
w_t^n(n', z, g) &= \frac{\alpha\phi}{1-\phi+\alpha\phi} a_t z (n')^{\alpha-1} + (1-\phi)(b + \Omega_t(g)) - \phi\chi_{gz} \\
w_t^h(\bar{x}_g, n', z, g) &= \bar{x}_g \frac{\alpha\phi}{1-\phi+\alpha\phi} a_t z (n')^{\alpha-1} + (1-\phi)(b + \Omega_t(g)) - \phi\chi_{gz}
\end{aligned}$$

So far, I have assumed that firms can only observe the new hire status and not the worker's individual productivity. If I relax that assumption, workers are instead paid

$$w_t^h(x, n', z, g) = x \frac{\alpha\phi}{1-\phi+\alpha\phi} a_t z (n')^{\alpha-1} + (1-\phi)(b + \Omega_t(g)) - \phi\chi_{gz},$$

where the first term depends on their individual expected productivity. In this case, the marginal hire at each type of firm is indifferent between accepting the offer and remaining unemployed. There is a positive surplus for all workers with a higher than marginal productivity.

B.2. Parameter sensitivity to racial gaps

The racial gaps in employment and sorting in the data are large, at -4.1% and 6.2%, respectively. This leads the estimates for the parameters governing racial disparities to be quite large. Table B.1 reports the estimated parameters under varying assumptions about the employment and sorting gaps, holding the other gap fixed at the value from the data.

Table B.1: Parameter sensitivity to racial gaps in employment and sorting

(a) Varying racial employment gap

	-1%	-2%	-3%	-4.1%
Callback gap				
λ_{abs}	0.909	0.846	0.790	0.736
λ_{rel}	1.030	1.025	1.021	1.016
Statistical discrimination				
Δp_L	0.125	0.193	0.255	0.315
Δp_S	0.488	0.595	0.696	0.798
Taste-based discrimination				
$\Delta \chi_L$	0.010	0.013	0.016	0.018
$\Delta \chi_S$	0.041	0.047	0.052	0.057

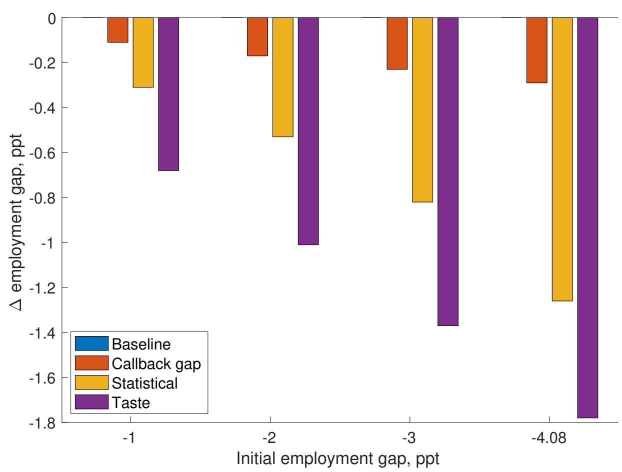
(b) Varying large firm sorting gap

	1%	2%	3%	4%	5%	6.2%
Callback gap						
λ_{abs}	0.742	0.741	0.740	0.738	0.737	0.736
λ_{rel}	0.982	0.989	0.995	1.002	1.008	1.016
Statistical discrimination						
Δp_L	0.293	0.299	0.304	0.308	0.312	0.315
Δp_S	0.564	0.613	0.660	0.705	0.749	0.798
Taste-based discrimination						
$\Delta \chi_L$	0.017	0.017	0.017	0.018	0.018	0.018
$\Delta \chi_S$	0.046	0.048	0.051	0.053	0.055	0.057

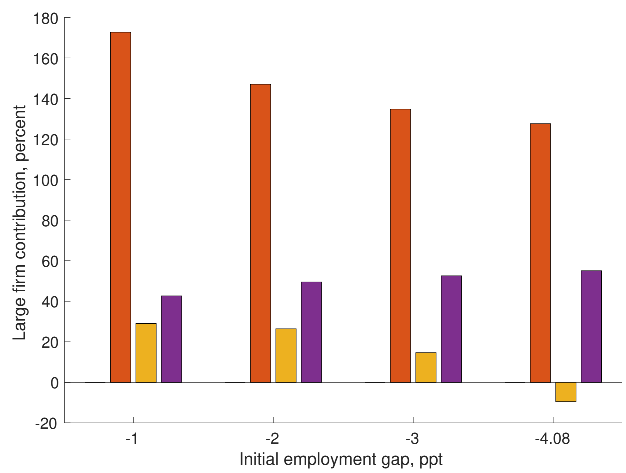
In the callback gap model, the absolute parameter is mostly determined by the overall employment gap. The parameter estimates imply that the matching rate gap varies from 12% to 43% as the employment gap moves from -1% to -4.1%. The benchmark callback gap in the correspondence literature is about 36% (Quillian *et al.*, 2017). Similarly, the relative parameter is more heavily influenced by the degree of sorting. In the statistical discrimination model, the gap in signal quality at large firms is high to match the wide employment gap. For small firms, the parameter gets smaller if either gap narrows, but especially the employment gap, as this governs the overall scale of the friction. The taste-based model is similar, with the large-firm friction mostly governed by the overall employment gap and the small-firm friction attenuating as either gap narrows.

Figure B.1: Comparison of steady states with alternative targeted moments

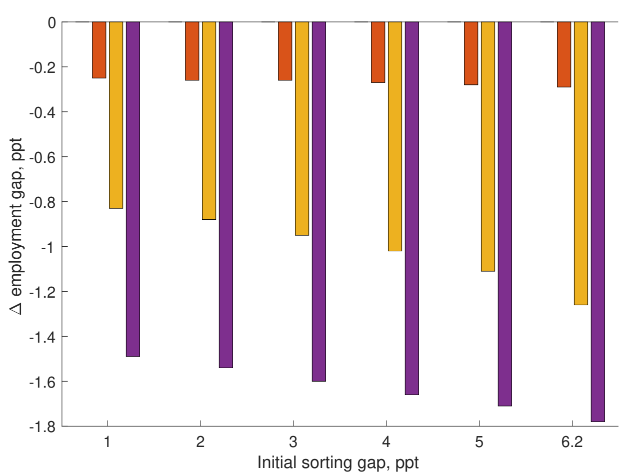
(a) Change in employment gap



(b) Percent contribution of large firms



(c) Change in employment gap



(d) Percent contribution of large firms

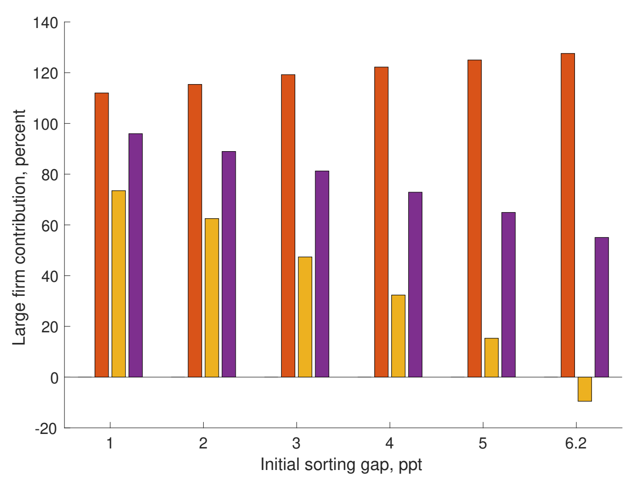


Figure B.1 shows how these alternative parameter estimates affect the counterfactual results, both the change in the racial employment gap and the conribution of large firms to this change. Across all of these alternative calibrations, the racial employment gap worsens in the low productivity steady state. The magnitudes increase as initial gaps in employment and sorting widen, reflecting stronger frictions. The contribution of large firms varies across specifications. In the callback gap model, large firms always contribute more than 100% to the total change in the employment gap. This is because the relative outside option channel is the only channel operating for these firms once they receive a match, so the relative wage effects described in the previous discussion are always most important.

In the statistical and taste-based discrimination models, large firms contribute less than their 64% employment share across all smaller employment gap calibrations. This is because the frictions for hiring Black workers at small firms have to be relatively strong to generate the 6.2% sorting gap, leading them to be more responsive to changes in productivity. When the degree of sorting is lower, as we move from right to left in Panel (d), large firms are relatively more important for the total change in the employment gap. Thus, the contribution of large firms to the change in the racial employment gap in a slack versus tight labor market depends crucially on why large firms employ more Black workers and to what extent this sorting occurs.

B.3. Model without wage discrimination

In this section, I extend the baseline model to consider a case in which firms must pay all workers the same wage, conditional on productivity. Under this assumption, the firm's problem is the same, except the wages become

$$w_t^n(n', z, \{n_g\}) = \frac{\alpha\phi}{1-\phi+\alpha\phi} a_t z(n')^{\alpha-1} + (1-\phi)\left(b + \sum_g \frac{n_g}{n}\Omega_t(g)\right) - \phi\left(\sum_g \frac{n_g}{n}\chi_{gz}\right) \tag{B.1}$$

$$w_t^h(x, n', z, \{h_g\}) = x\frac{\alpha\phi}{1-\phi+\alpha\phi} a_t z(n')^{\alpha-1} + (1-\phi)\left(b + \sum_g \frac{h_g}{h}\Omega_t(g)\right) - \phi\left(\sum_g \frac{h_g}{h}\chi_{gz}\right). \tag{B.2}$$

This setup is equivalent to assuming that the firm does not observe the race of workers during bargaining and that they are unable to make inference about the worker's race based on their productivity.

I recalibrate the model with this assumption. All equilibrium conditions are the same as the baseline, except that Equations (B.1) and (B.2) replace Equations (19) and (20). The parameter estimates are reported in Table B.2. The baseline calibration is the same as in Table 6, as there are no differences between Black and white workers in this model so the constraint on wage discrimination is not binding. For the models with racial disparities, the parameters that govern these disparities are less severe than when firms are allowed to pay different wages, especially for large firms. For example, the average match rate gap falls to 32% from 43% in the callback gap model, driven by a drop from 40% to 27% at large firms. In the statistical discrimination model, large firms now place 16% more weight on the Black population mean rather than individual resumes, rather than 32%. In the taste-based model, the taste costs now amount to 0.04% and 0.45% of the aggregate large and small-firm wage bills. The frictions are less severe for large firms, because the wage spillover channel is much more muted when workers are paid the same wage and their outside options only differ in the probability of receiving that wage.

The model matches the targeted moments exactly in the alternative calibration. Table B.3 reports the untargeted moments. The callback gap model has slightly larger job-finding gaps when firms are constrained to pay the same wages. This is because firms are more selective about hiring Black workers when they are not able to pay them less. More selectivity

Table B.2: Fitted parameters, no wage discrimination

Parameter	Meaning	Baseline	Callback gap	Statistical	Taste
Scale parameters					
μ	Number firms/worker	0.009	0.009	0.009	0.009
b	Flow value unemp	0.981	0.982	0.985	0.980
ϕ	Bargaining power	0.351	0.350	0.335	0.362
Estimated parameters					
δ	Exog. separation	0.024	0.024	0.024	0.024
$c_v(L)$	Vacancy cost	0.013	0.013	0.014	0.013
$c_v(S)$	Vacancy cost	0.186	0.187	0.140	0.186
$\frac{z_L}{z_S}$	Relative productivity	4.081	4.081	4.113	4.058
Worker disparity parameters					
λ_1	Match gap	1	0.790	1	1
λ_2	Match bias, large	1	1.031	1	1
Δp_L	Signal gap, large	0	0	0.165	0
Δp_S	Signal gap, small	0	0	0.649	0
$\Delta \chi_L$	Taste penalty, large	0	0	0	0.003
$\Delta \chi_S$	Taste penalty, small	0	0	0	0.041

worsens the job-finding gaps but improves the separation gaps because the only source of endogenous separations is workers who are revealed to be unproductive, which declines with selectivity. For the statistical discrimination model, the job-finding gaps turn negative, because the wage channel is not incentivizing firms to hire as many Black workers, which also leads the separation gap to narrow. The job-finding and separation gaps in the taste-based discrimination model are not affected by the constraint to pay the same wages because the direct taste costs are relatively more important than the wage gaps in this model.

Table B.3: Untargeted moments, no wage discrimination

Moment	Data	Baseline	Callback gap	Statistical	Taste
Separation rate					
Large	3.05	2.83	2.83	2.83	2.83
Small	4.07	3.77	3.77	3.77	3.77
Job-finding gap (B-W)					
Large	0.64	0.00	-0.71	-0.23	-0.95
Small	-1.72	0.00	-1.69	-0.24	-2.42
Separation gap (B-W)					
Large	0.14	0.00	0.06	0.29	-0.06
Small	0.12	0.00	0.03	1.57	-0.76

The units are percentage points. The data moments are all calculated in the SIPP.