

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. The statistical discrimination channel is most important for generating this effect in the calibrated model.

JEL: E24, J63, J71, M51

Keywords: Racial employment gap, firm heterogeneity, search and matching

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1. Introduction

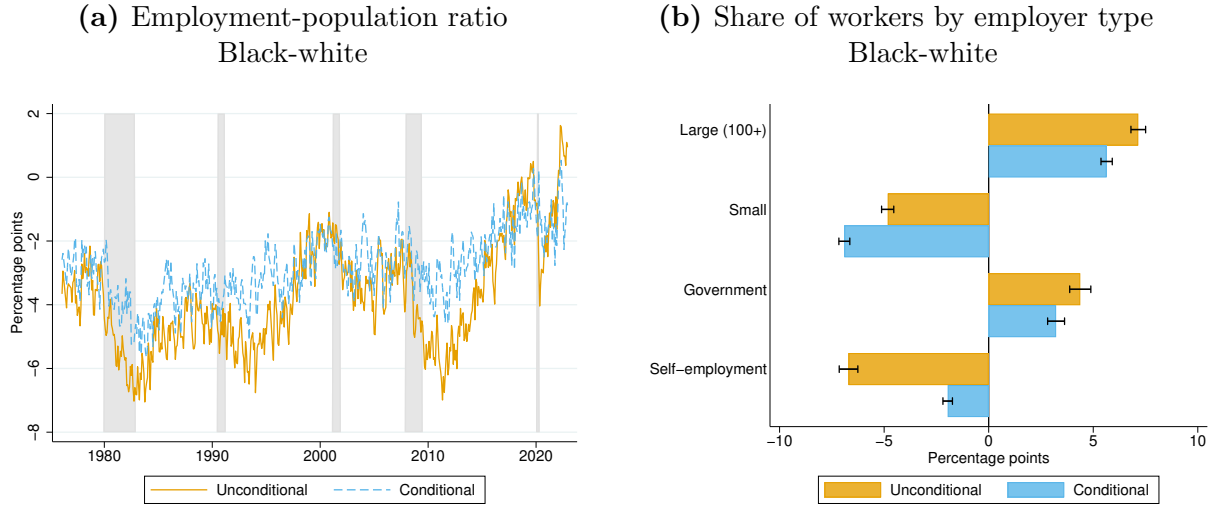
The Black population in the U.S. faces persistently lower rates of employment than the white population. Additionally, Black employment responds more to macroeconomic conditions, rising more during expansions but also falling more during contractions. For example, over the peak to trough of the Great 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 composition, 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 additional barriers in hiring. 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 be less effective at stabilizing

¹Mean 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.

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

Figure 1: Racial gaps in employment and employer composition



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.

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.

³For 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), wealth inequality (Derenoncourt *et al.*, 2024), and many more. In the model, I allow for rich interactions among three sources of racial distortions and I use the calibration to discipline the relative magnitudes of each channel. (1) I allow firms to receive noisier signals about Black applicants, particularly at small firms, meant to capture statistical discrimination. This channel could be microfounded with differences in professional networks or differences in monitoring practices which can lead to statistical dis-

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

crimination as in [Cavounidis *et al.* \(2024\)](#). (2) I allow firms to have utility costs associated with employing workers by race, meant to capture taste-based discrimination. This channel would be consistent with small firms being more influenced by taste preferences of management and facing less legal scrutiny from the EEOC, enabling them to discriminate more. (3) I allow the composition of matches to be distorted by the composition of incumbent employment. This acts as a co-racial hiring channel ([Miller & Schmutte, 2023](#), [Sorkin, 2025](#)). Each of these channels leads to lower employment for Black workers and sorting towards large firms. 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. Incumbency bias in matching rates amplifies either form of discrimination.

Finally, I calibrate the model to match moments from the micro-data. I find that the statistical discrimination channel is most important for reproducing the employment gap, while the incumbency bias in matching rates is most important for sorting patterns. I use the model to 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 by 1.37 percentage point in the lower productivity steady state, more than double the decrease from the empirical section of 0.64 percentage point. Qualitatively, the model captures that the worse employment gap is driven by a worse gap at large firms. 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 they are more exposed to large firms (composition effect) and large firms adjust their hiring behavior by more (policy effect). The most important features for generating this result more broadly are the wage channel that allows for spillovers between small-firm and large-firm hiring decisions and the degree of selectivity over matches. High selectivity serves to amplify disparities caused by statistical discrimination.

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 & Chanci (2021). Another related area of research considers the effects of monetary policy on racial inequality (see Bartscher *et al.*, 2021; Lee *et al.*, 2025; 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 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), Miller & Schmutte (2023), and Sorkin (2025). The correspondence study literature has show empirical racial disparities by firm size. 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. Empirically, Boulware & Kuttner (2019) finds that discrimination charges are countercyclical. My paper builds on these studies by incorporating heterogeneous discrimination by firm size in a frictional labor market model. A related paper by Sorkin (2025) uses a model with both statistical and taste-based discrimination to study racial gaps in separations and the implications for racial earnings gaps. On the theory side, my model also incorporates both channels and uses the difference in early separation rates to identify statistical discrimination. My focus is on understanding how racial employment gaps change with aggregate economic conditions,

particularly across the firm size distribution.

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 ([US Census Bureau, 2023](#)). 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

⁵The 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.

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. 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,

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

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



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.

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

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 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,

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

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 term. 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

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

Table 1: Employment shares and variance decomposition

(a) Large firm share			(b) Variance decomposition, HP-filter			
	Black	White		Composition	Excess large	Error
Employment	69.4	53.9	Employment	3.3	6.4	-0.6
Hires	63.9	47.4	Hires	10.6	8.2	1.1
Separations	64.9	48.7	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 the contribution of large firms in excess of their relative share of employment, hires, or separations. The units are percentage points.

firms is also larger for hires and separations across both specifications.

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 (US Census Bureau, 1996). 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.

⁸For 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.

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 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.

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

¹⁰This 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.

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 I also classify separations that I do not observe end dates for as involuntary if the worker is unemployed 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,

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

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

¹¹Reasons for involuntary separations include: on layoff, discharged/fired, employer bankrupt, employer sold business, job was temporary and ended, slack work or business conditions.

the difference is not statistically significant for large firms.

Table 2: Employment fluctuations by firm type

(a) Individual controls					
	(1)	(2)	(3)	(4)	(5)
	All	Large	Small	Government	Self
Black	-4.08 (0.22)	2.65 (0.31)	-7.31 (0.25)	2.73 (0.22)	-2.04 (0.17)
UR	-1.20 (0.13)	-0.52 (0.13)	-0.50 (0.11)	-0.06 (0.08)	-0.14 (0.09)
Black \times UR	-0.64 (0.21)	-0.42 (0.28)	0.24 (0.21)	-0.70 (0.19)	0.22 (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)	(2)	(3)	(4)	(5)
	All	Large	Small	Government	Self
UR	-1.49 (0.27)	-1.30 (0.16)	-0.30 (0.11)	0.03 (0.07)	0.02 (0.06)
Black \times UR	-0.64 (0.29)	-0.62 (0.27)	0.27 (0.25)	-0.34 (0.16)	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.

Given the panel structure of the SIPP, I can analyze how changes in the state unemployment rate affect employment outcomes within individuals using a fixed effects specification,

$$E_{ijt} = \alpha_{ij} + \beta_j UR_t + \beta_j^B \text{Black} \times UR_t + \epsilon_{ijt}, \quad (4)$$

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 an 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

Table 3: Job inflows by firm type**(a) Hires (percent of population)**

	(1)	(2)	(3)	(4)	(5)	(6)
	All	Large	Small	All	Large	Small
Black	0.04 (0.04)	0.32 (0.03)	-0.31 (0.02)			
UR	-0.11 (0.03)	-0.08 (0.02)	-0.05 (0.01)	-0.14 (0.10)	-0.14 (0.05)	-0.02 (0.03)
Black \times UR	-0.08 (0.03)	-0.10 (0.03)	0.01 (0.02)	-0.23 (0.08)	-0.15 (0.06)	-0.09 (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)	(2)	(3)	(4)	(5)	(6)
	All	Large	Small	All	Large	Small
Black	-2.13 (0.19)	0.09 (0.13)	-2.01 (0.10)	-8.07 (0.42)	-2.22 (0.32)	-5.17 (0.24)
UR	-1.14 (0.18)	-0.64 (0.09)	-0.43 (0.07)	-5.27 (0.26)	-2.86 (0.16)	-2.01 (0.13)
Black \times UR	-0.18 (0.15)	-0.28 (0.11)	0.11 (0.08)	1.63 (0.30)	0.27 (0.23)	1.25 (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.

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 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) restrict 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.

Table 4: Separation rates by firm type

	(1)	(2)	(3)	(4)	(5)	(6)
	All	Large	Small	All	Large	Small
Black	0.26 (0.05)	0.40 (0.06)	0.51 (0.11)	0.35 (0.03)	0.45 (0.04)	0.52 (0.07)
UR	-0.03 (0.04)	-0.05 (0.04)	0.00 (0.05)	0.18 (0.02)	0.18 (0.03)	0.29 (0.03)
Black \times UR	-0.03 (0.04)	-0.10 (0.06)	0.03 (0.10)	-0.01 (0.03)	-0.00 (0.04)	-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.

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. 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 . Workers are ex-ante identical. I give three possible channels for racial disparities in the model: (1) firms receive noisier information about Black candidates, as in the statistical discrimination literature; (2) firms have a disutility for employing Black workers, as in the taste-based discrimination literature; (3) the racial composition of matches is skewed towards the racial composition of incumbent employment, to provide an avenue for coracial hiring.

Firms There are two types of firms indexed by their idiosyncratic productivity z , which I assume to be fixed. There is no firm entry or exit in this model. Let $\nu(z)$ be the share of firms with productivity z . 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). 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.

Matches are allocated via random search with a distortion towards the racial composition of employment, meant to reflect that firms that have a higher share of Black employment may attract more Black matches, for example due to differences in network effects as in Miller & Schmutte (2023). Without this channel, firms would sample workers proportional to their share in the unemployed pool and workers would sample firms proportional to their share of the total vacancies. For each firm, I allow the total number of matches to be the same as the undistorted case, i.e. each firm has probability $q(\theta)$ of meeting a worker, but I allow the composition of matches to skew towards the racial composition of employment. I define the number of matches between a worker from group g and a firm of productivity z to be $q(\theta)v_z\lambda_{gz}$, with

$$\lambda_{gz} \equiv \lambda \frac{n_{gz}}{n_z} + (1 - \lambda) \frac{u_g}{u}$$

The parameter λ governs the degree of distortion in matching. I assume that firms take λ_{gz} as given and do not internalize the effect of hiring an additional group g worker on future

recruitment.

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

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

I allow this probability to vary by race and firm type, p_{gz} . This allows for a statistical discrimination channel in the model, where firms may receive noisier information about one group, leading them to place more weight on the population mean than the individual’s qualifications (e.g. [Black, 1995](#), [Lang & Lehmann, 2012](#)). Differences in noise could also capture differences in referral networks if these 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. The final racial disparity I allow for in the model is taste-based discrimination, where firms have utility costs over groups of workers, χ_{gz} . I assume these are paid for all incumbent

¹²This 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.

workers and new hires at the production stage. I anticipate stronger taste costs for Black workers at small firms, which could arise if small firms have stronger preferences for hiring workers of the same race, given the higher prevalence of white-owned businesses. 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, 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,

$$J_t(n_B, n_W, z) = \max_{v \geq 0, x_g^*} -c_v(z)v + a_t z (n')^\alpha - \sum_g ((1 - \delta)n_g + h_g) \chi_{gz} \quad (6)$$

$$- \sum_g ((1 - \delta)n_g w_t^n(n', z, g) + h_g w_t^h(x_g^*, n', z, g)) + \beta \mathbb{E}_t J_{t+1}(n'_B, n'_W, z)$$

¹³One 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.

such that

$$n' = \sum_g n'_g \tag{7}$$

$$n'_g = (1 - \delta)n_g + \lambda_{gz}q(\theta_t)v \int_{x \geq x_g^*} x dF(x|p_{gz}) \tag{8}$$

$$h_g = \lambda_{gz}q(\theta_t)v(1 - F(x_g^*|p_{gz})) \tag{9}$$

$$(1 - p_{gz})\mathbb{E}[x] \leq x_g^* \leq p_{gz} + (1 - p_{gz})\mathbb{E}[x] \tag{10}$$

where $w_t^n(\cdot)$ and $w_t^h(\cdot)$ are wages paid to incumbent 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. $F(x|p)$ 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.

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.

The firm's problem summarizes the three sources of racial disparities in the model. The number of hires depends on the distortion in matching rates, λ_{gz} . The threshold rules depend on the quality of the signal, p_{gz} . The composition of employment affects total taste costs, χ_{gz} . The three channels interact through the firm's problem to determine the equilibrium disparities in employment overall.

¹⁴With 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.

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,

$$V_t^n(n, g, z) = w_t^n(n, z, g) + \beta \mathbb{E}_t [V_{t+1}^u(g) + (1 - \delta)(V_{t+1}^n(n', g, z) - V_{t+1}^u(g))], \quad (12)$$

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,

$$V_t^h(x, n, g, z) = w_t^h(x, n, z, g) + \beta \mathbb{E}_t [V_{t+1}^u(g) + x(1 - \delta)(V_{t+1}^n(n', g, z) - V_{t+1}^u(g))], \quad (13)$$

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

$$V_t^u(g) = b + \beta \mathbb{E}_t V_{t+1}^u(g) \quad (14)$$

$$+ \underbrace{\beta \mathbb{E}_t \left[\theta_{t+1} q(\theta_{t+1}) \sum_z \tilde{\lambda}_{gz} \int_{x > x_{gz}^*} (V_{t+1}^h(x, n', g, z) - V_{t+1}^u(g)) dF(x|p_{gz}) \right]}_{\Omega_t(g)}$$

$$\tilde{\lambda}_{gz} = \lambda_{gz} \left(\frac{\mu_z v_z}{\sum_z \mu_z v_z} \right) \left(\frac{u_g}{u} \right)^{-1} \quad (15)$$

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, x_{gz}^* is the firm's equilibrium threshold rule, and $\tilde{\lambda}_{gz}$ is the matching distortion from the perspective of the worker. If there is no incumbent bias in matching, $\lambda = 0$, then $\lambda_{gz} = u_g/u$ and $\tilde{\lambda}_{gz}$ is equal to the vacancy share for type z firms. If $\lambda > 0$, then $\sum_z \tilde{\lambda}_{gz}$ may be higher or lower than 1 depending on whether group g is over- or under-represented in employment.

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 to the following rules

$$\phi D_{t,n_g} = (1 - \phi) (V_t^n(n', g, z) - V_t^u(g)) \quad (16)$$

$$\phi D_{t,x,g} = (1 - \phi) (V_t^h(x, n', g, z) - V_t^u(g)), \quad (17)$$

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,

$$w^n(n', z, g) = \frac{\alpha\phi}{1 - \phi + \alpha\phi} a_t z n'^{\alpha-1} + (1 - \phi)(b + \Omega_t(g)) - \phi\chi_{gz} \quad (18)$$

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

where $\Omega_t(g)$ is the value of searching next period for a worker from group g as defined in equation (14). 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.

Notice that the first component of the wage equation is a fraction of the marginal product of labor. The second component depends on workers' outside options. If groups face different prospects in the labor market, the second term will vary by group, and thus endogenous wage gaps may arise for workers with the same productivity. The third component represents the pass-through of taste-based discrimination, which can worsen wage gaps that arise from other channels.

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

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

$$u_{gt+1} = \pi(g) - \sum_z \mu_z \left(n'_{gz} + \lambda_{gz} q(\theta_t) v_z \int_{x \geq x_g^*} (1-x) dF(x|p) \right), \quad (20)$$

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

$$\Gamma(z) = \frac{\mu_z \sum_g ((1-\delta)n_{gz} + h_{gz})}{\sum_{\bar{z}} \mu_{\bar{z}} \sum_g ((1-\delta)n_{g\bar{z}} + h_{g\bar{z}})} \quad (21)$$

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 $V_t^n(n', g, z), V_t^h(x, n', g, z), V_t^u(g)$, (iv) wage functions $w_t^n(n', g, z), w_t^h(x, n', g, z)$, 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 $\theta, \{u_g, n_{gz}\}, \Omega_t(g), w_t^n(n', z, g)$, and $w_t^h(x, n', z, g)$, 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 $\theta, \Gamma(z), w_t^n(n', z, g), w_t^h(x, n', z, g)$, and $v_t(n_B, n_W, z), x_{tg}^*(n_B, n_W, z)$, worker value functions $V_t^n(n', g, z), V_t^h(x, n', g, z)$, and $V_t^u(g)$ solve the worker problem and $\Omega_t(g)$ is consistent with value functions;
3. *Wage bargaining*: $w_t^n(n', z, g), w_t^h(x, n', z, g)$ 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 un-employment 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,

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

where

$$\begin{aligned}
C_t(\Delta_B, \Delta_W) &= \min_{\{x_g^*\}} \sum_g \Delta_g \frac{c_v(z)}{q(\theta_t) \int_{x \geq x_g^*} x dF(x|p_{gz})} \\
&\quad + \Delta_g \frac{\int_{x \geq x_g^*} (1-x) dF(x|p)}{\int_{x \geq x_g^*} x dF(x|p_{gz})} (1-\phi)(b + \Omega_t(g) + \chi_{gz}) \quad (22)
\end{aligned}$$

s.t.

$$\frac{\Delta_B}{\lambda_{Bz} \int_{x \geq x_B^*} x dF(x|p_{gz})} = \frac{\Delta_W}{\lambda_{Wz} \int_{x \geq x_W^*} x dF(x|p_{gz})} \quad (23)$$

and $C_t(\Delta_B, \Delta_W)$ can be understood as the total cost of hiring $\Delta_B + \Delta_W$ *productive* workers. The first term inside the cost minimization sum is the total expenditure on vacancies that match to group g workers. The second term is the total expenditure on outside option compensation and taste costs for workers who are not productive. Consider the limit as x_g approaches the upper bound. The first term will go to infinity as the number of vacancies

needed to get Δ_g productive workers goes to infinity. The second term will go to zero. As x_g approaches the lower bound, the first term goes to $\frac{c_v(z)}{q(\theta)\bar{x}}$, which is the minimum possible expenditure on vacancies. The second term goes to $\frac{1-\bar{x}}{\bar{x}}(1-\phi)(b+\Omega_t(g)+\chi_{gz})$, which is the maximum possible expenditure on unproductive compensation and taste costs, reflecting unconditional probabilities. The cost-minimizing threshold, x_g^* lies somewhere between the two extremes.

Finally, the constraint (23) reflects the implications of random search: firms cannot post separate vacancies for different groups of workers. Hiring an additional productive worker from one group increases the vacancy posting expenditure for the other group, since some of the additional vacancies will match to other workers.

The cost minimization solution captures the tradeoff between vacancy posting and compensation costs,

$$\frac{c_v(z)}{q(\theta_t)} = \sum_g \lambda_{gz}(1-\phi)(b+\Omega_t(g)+\chi_{gz})\frac{1}{x_g^*} \left(\int_{x \geq x_g^*} x dF(x|p_{gz}) - x_g^*(1-F(x_g^*|p_{gz})) \right) \quad (24)$$

The left side of equation (24) is the marginal vacancy cost, times the expected duration of the vacancy. The right side of equation (24) captures the compensation costs between the average hire and the marginal hire and is monotonically decreasing in x_g^* . With only one group, equation (24) would pin down the hiring threshold independently of productive hires, Δ , as in Baydur (2017). With two groups, the threshold decisions are jointly determined by equations (23) and (24), and the threshold rule depends on relative productive hires between the two groups due to spillovers from random search.

For an interior solution, the firm will add productive hires until the shadow value of an additional group g worker, Λ_{gt} , is equal to the marginal cost of hiring another:

$$\Lambda_{gt} = \frac{\partial C_t(\Delta_B, \Delta_W)}{\partial \Delta_g} \quad (25)$$

$$\Lambda_{gt} = \frac{\alpha(1-\phi)}{1-\phi+\alpha\phi} a_t z (n')^{\alpha-1} - (1-\phi)(b+\Omega_{t+1}(g)+\chi_{gz}) + \beta(1-\delta)\mathbb{E}_t[\Lambda_{gt+1}], \quad (26)$$

where the shadow value of a type g worker is equal to the marginal product of labor net of

wages plus the expected shadow value of that worker in the next period.

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 calibrate the remaining parameters to match moments from the data using generalized method of moments.

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.¹⁶ 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.¹⁷

4.2. Fixed parameters

The top panel of 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

¹⁶With 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).

¹⁷Using the coefficient estimates from the first row of Table 2, $2.32 = \frac{2.65}{2.65-7.31} \times -4.08$.

of 0.012. I set the production curvature α to 0.677, as is common in the RBC literature. I use a standard Cobb-Douglas matching technology, $q(\theta) = \zeta\theta^{-\psi}$, with matching elasticity $\psi = 0.6$, as in [Petrongolo & Pissarides \(2001\)](#).

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, such that statistical discrimination arises from the gap in signal qualities between workers across groups within the same firm.

The masses of high and low productivity firms are fixed in the model, but employment at each type of firm adjusts endogenously. I set the share of high-productivity 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. Given the endogenous relative employment shares, 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](#).

4.3. Fitted parameters

The calibrated parameters affect all moments, but I give a sense of the identification for each. The parameter values are summarized in the bottom panel of [Table 5](#).

Table 5: Model Parameters

Parameter	Meaning	Value	Target
<i>Fixed Parameters</i>			
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
v	Share of high-productivity 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)
<i>Fitted Parameters</i>			
ζ	Matching scale	0.642	Hired share of matches 0.2
μ	Number firms/worker	0.009	Market tightness 0.72
b	Flow value unemp	0.979	Normalize outside option
ϕ	Bargaining power	0.360	Ratio b to avg prod
δ	Exog. separation	0.024	Average separation rate
$c_v(L)$	Vacancy cost	0.012	Large-firm job-finding rate
$c_v(S)$	Vacancy cost	0.196	Small-firm job-finding rate
$\frac{z_L}{z_S}$	Relative productivity	4.067	Relative large-firm employment
λ	Matching distortion	0.630	Large-firm contact gap, Kline et al. (2022)
Δp_L	Signal gap, large	0.186	Separation gap, large
Δp_S	Signal gap, small	0.285	Separation gap, small
$\Delta \chi_L$	Taste penalty, large	0.003	Sorting gap
$\Delta \chi_S$	Taste penalty, small	0.013	Employment gap

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,

$$\zeta \theta^{1-\psi} \sum_z \sum_g \lambda_{gz} \frac{v(z)}{v} (1 - F(x_{gz}^* | p_{gz})).$$

Thus, given a target for the job-finding rate, 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 target 20% as the weighted average of the hired share of matches, which is consistent with firms interviewing around five applicants before making an offer, as in [Barron et al. \(1997\)](#)

or [Villena-Roldan \(2012\)](#).

Aggregation across firms means that market tightness is given by

$$\theta = \frac{\mu(vv_L + (1 - v)v_S)}{u_B + u_W},$$

thus the exogenous mass of firms is important for scaling market tightness. I target a market tightness of 0.72 as in [Elsby & Michaels \(2013\)](#).

Following the strategy of [Baydur \(2017\)](#), I use a normalization for b such that the equilibrium value of unemployment for white workers ($b + \Omega(W)$) is equal to 1 and I discipline ϕ by targeting 0.73 for the ratio of the flow value of unemployment, b , to average productivity (Y/N). To see the intuition, consider the shadow value of a white worker in equation 26 and suppose ϕ rises. All else equal, the second term will become smaller in absolute value, so for the shadow value to remain constant, the first term must also fall. This means employment will rise, leading to a decrease in average productivity and an increase in the ratio of b to Y/N .

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. As the vacancy cost increases, the firm posts fewer vacancies and job-finding falls. 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.

I now turn to the parameters that govern disparities between racial groups. I calibrate the matching distortion towards incumbent employment, λ to target the contact gap at large firms documented by [Kline *et al.* \(2022\)](#). In the model, I define the contact gap by firm type to be the gap in matching rates for white workers relative to Black workers at each type of

firm,

$$\frac{\lambda_{Wz}/u_W}{\lambda_{Bz}/u_B} - 1 = \frac{\lambda \frac{n_{Wz}}{n_z} \left(\frac{u_W}{u}\right)^{-1} + 1 - \lambda}{\lambda \frac{n_{Bz}}{n_z} \left(\frac{u_B}{u}\right)^{-1} + 1 - \lambda} - 1$$

Without any other differences between groups, λ will not generate a contact gap because $\frac{n_{gz}}{n_z} \left(\frac{u_g}{u}\right)^{-1} = 1$. Similarly, there will be no contact gap if $\frac{n_{gz}}{n_z} \left(\frac{u_g}{u}\right)^{-1} \neq 1$ unless $\lambda > 0$. In partial equilibrium, the contact gap is increasing in λ . In general equilibrium, higher λ affects the composition of incumbent employment relative to unemployment as well.

Both statistical discrimination and taste-based discrimination would lead to worse average employment for Black workers and more sorting towards large firms if the frictions are stronger at small firms. I separately identify the channels by targeting separation gaps as well. For statistical discrimination, I normalize the signal quality for white workers to be $p_{Wz} = 0.99$, such that what matters is the gap in signal quality between Black and white workers, $\Delta_z = p_{Wz} - p_{Bz}$. For taste-based discrimination, I normalize $\chi_{Wz} = 0$, such that χ_{Bz} can be interpreted as the relative taste costs of employing a Black worker over a white worker.

To understand the identification of each channel, first consider a model with just taste-based discrimination. Stronger taste frictions would lead firms to be more selective about hiring Black workers because of the direct costs of employing them. The direct effect would be unambiguously lower job-finding and employment rates and also lower separation rates for Black workers, as the higher selectivity means the marginal Black applicant is more positively selected and therefore less likely to separate. The statistical discrimination parameters are important for generating positive separation gaps. Lower information quality about Black applicants means that even if firms set the same cutoff x^* across both groups, more Black workers will be revealed to be unproductive because the signal is noisier.¹⁸ Without differences in signal quality, if a firm is more selective about hiring it necessarily implies lower separation rates for the affected group. This friction breaks that relationship, which allows the model to match both negative job-finding gaps and positive separation gaps.

¹⁸This is the same result from [Morgan & Várdy \(2009\)](#).

Table 6: Moments**(a)** Aggregate moments

Moment	Data	Model
Employment share		
Large	0.64	0.64
Job-finding rate, ppt		
Large	6.45	6.42
Small	4.78	4.83
Separation rate, ppt	3.17	3.17
Large	3.05	2.81
Small	4.07	3.81
External		
Hired share matches	0.20	0.20
Market tightness	0.72	0.72
Outside option	1.00	1.00
Ratio b to avg prod	0.73	0.73
Vacancy yield	1.30	0.19
Vacancy yield, Large	0.70	0.13

(b) Racial gap moments

Moment	Data	Model	No matching distortion	No statistical	No taste
Employment, ppt (B-W)					
Empl rate	-4.08	-4.09	-2.79	0.32	-3.49
Large-firm share	6.20	6.19	0.61	4.80	2.44
Job-finding, ppt (B-W)					
Large	0.10	-0.04	-0.22	0.64	-0.20
Small	-2.23	-1.27	-0.28	-0.73	-0.49
Separation, ppt (B-W)					
Large	0.40	0.38	0.33	0.02	0.38
Small	0.51	0.49	0.46	-0.14	0.67
Contact gap	0.36	0.13	0.00	-0.03	0.12
Large firms	0.09	0.09	0.00	-0.05	0.11

The figures in bold represent untargeted moments. The data moments are all calculated in the SIPP except for the external moments and contact gaps.

The model fits the targeted moments closely, as shown in Table 6. I match the average separation rate by construction, but the model matches the distribution across firm size reasonably well. I don't target any moments related to vacancies. For comparison, I define the model counterpart of the vacancy yield from [Davis *et al.* \(2013\)](#) as $\sum_g h_{gz,t}/(v_{z,t-1} -$

$\sum_g h_{gz,t-1}$), reflecting the total number of hires relative to unfilled vacancies in the previous month. The scale of the model is off, likely reflecting the monthly periodicity of the model. However, the model matches that the vacancy yield is higher for small firms than large firms. The ratio of the vacancy yield for large firms relative to the aggregate is 0.68 in the model and 0.54 in the data.

To benchmark how well the contact gap in the model overall matches the data, I compare the size of the aggregate gap to the average 36% gap in the correspondence study literature, as surveyed by [Quillian *et al.* \(2017\)](#). As a more conservative approach, I report the aggregate gap in the model as the weighted average of small and large firms using vacancy shares as weights. This leads the aggregate number to skew closer to the gap for large firms. If I compute the aggregate gap using the relative masses of firms instead, the model counterpart is 28%.

The racial gaps in the model are determined by the interaction of the bias in vacancy matching towards the composition of incumbent employment and the two forms of discrimination. Panel (b) of [Table 6](#) shows what happens to each of these gaps when one of the three elements is removed. Removing the matching distortion almost entirely removes the sorting towards large firms. Removing one of the channels of discrimination leads to less sorting, particularly taste-based discrimination. Meanwhile, removing statistical discrimination reverses the employment gap. Without statistical discrimination, small firms are much more selective about hiring Black workers due to taste-based discrimination. This lowers equilibrium wages, which leads large firms to hire relatively more Black workers. Without statistical discrimination, this decrease in selectivity leads to higher Black employment at large firms, and is reinforced by the matching distortion.

5. Counterfactuals

5.1. Permanent decrease in aggregate productivity

I use the calibrated 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 2.¹⁹

Table 7 reports the results of this exercise. By construction, the data and model match exactly in the first row for the total change in employment for white workers. 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.

Table 7: Steady state comparison

<i>Changes: low - high productivity</i>		
	Data	Model
White employment rate	-1.49	-1.49
Large	-1.21	-1.04
Small	-0.28	-0.45
Employment gap	-0.64	-1.37
Large	-1.14	-1.43
Small	0.50	0.06

This table shows the comparison between the low productivity relative to high productivity steady state. The units are percentage points. The low productivity is 0.012 log points below high productivity, chosen such that the difference in the white employment rate in the first row matches between data and 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.

¹⁹This results in a 0.012 log point decrease in productivity.

The second group of Table 7 shows the difference in the racial employment gap between steady states. The model overestimates the negative impact on employment for Black workers, but captures that the decrease in employment is driven by large firms.

5.2. Decomposition

The calibrated model shows that a decrease in aggregate productivity worsens the employment gap at large firms, whereas it improves the gap slightly at small firms. In this section, I show why that happens, and what conditions need to be true for it to generalize outside of the model.

The employment-population rate in the model, epop_{gz} can be decomposed into productive employment-population, epop_{gz}^P , which I will call “permanent” employment, and temporary hires that are quickly revealed to be unproductive, epop_{gz}^T . The random search assumption, as shown in equation 23, lets us write the gap in employment rates into the component that comes from productive employment and the component that comes from temporary hires,

$$\begin{aligned} \text{egap}_z = \text{epop}_{Bz} - \text{epop}_{Wz} = & \text{epop}_{Wz}^P \left(\frac{1 - \pi}{\pi} \frac{\lambda_{Bz}}{1 - \lambda_{Bz}} \frac{\int_{x \geq x_{Bz}^*} x dF(x|p_{Bz})}{\int_{x \geq x_{Wz}^*} x dF(x|p_{Wz})} - 1 \right) \\ & + \text{epop}_{Wz}^T \left(\frac{1 - \pi}{\pi} \frac{\lambda_{Bz}}{1 - \lambda_{Bz}} \frac{\int_{x \geq x_{Bz}^*} (1 - x) dF(x|p_{Bz})}{\int_{x \geq x_{Wz}^*} (1 - x) dF(x|p_{Wz})} - 1 \right), \end{aligned} \quad (27)$$

where π is the Black share of the population in the model, λ_{Bz} is the Black share of matches at firm type z based on the Black share of unemployment and the distortion towards the Black share of incumbent employment. The first term in parentheses captures Black workers’ representation in productive employment relative to white workers. Black workers are over-represented when they are over-represented in matches ($\lambda_{Bz} > \pi$) and/or over-represented in productive hires per match.

Using this decomposition, I can write the change in the employment gap by firm size as

$$\begin{aligned}
\Delta \text{egap}_z = & \underbrace{\left(\Delta \text{epop}_{Wz}^P \right) \times \left(\frac{1 - \pi}{\pi} \frac{\lambda_{Bz}}{1 - \lambda_{Bz}} \frac{\int_{x \geq x_{Bz}^*} x dF(x|p_{Bz})}{\int_{x \geq x_{Wz}^*} x dF(x|p_{Wz})} - 1 \right)}_{\text{composition effects, permanent employment}} \\
& + \underbrace{\left(\Delta \text{epop}_{Wz}^T \right) \times \left(\frac{1 - \pi}{\pi} \frac{\lambda_{Bz}}{1 - \lambda_{Bz}} \frac{\int_{x \geq x_{Bz}^*} (1 - x) dF(x|p_{Bz})}{\int_{x \geq x_{Wz}^*} (1 - x) dF(x|p_{Wz})} - 1 \right)}_{\text{composition effects, temporary employment}} \\
& + \underbrace{\text{epop}_{Wz}^P \times \Delta \left(\frac{1 - \pi}{\pi} \frac{\lambda_{Bz}}{1 - \lambda_{Bz}} \frac{\int_{x \geq x_{Bz}^*} x dF(x|p_{Bz})}{\int_{x \geq x_{Wz}^*} x dF(x|p_{Wz})} \right)}_{\text{policy effects, permanent employment}} \\
& + \underbrace{\text{epop}_{Wz}^T \times \Delta \left(\frac{1 - \pi}{\pi} \frac{\lambda_{Bz}}{1 - \lambda_{Bz}} \frac{\int_{x \geq x_{Bz}^*} (1 - x) dF(x|p_{Bz})}{\int_{x \geq x_{Wz}^*} (1 - x) dF(x|p_{Wz})} \right)}_{\text{policy effects, temporary employment}}, \tag{28}
\end{aligned}$$

where the first two lines show the composition effects broken down by permanent and temporary employment and the last two lines show the policy effects. The composition effects hold fixed the representation of Black workers relative to white workers at each type of firm and each category of employment and adjust the employment rate for white workers. The policy effects hold fixed the employment of white workers in each category and adjust the representation of Black workers, representing the effects of firm policy changes.

The composition effects of permanent employment are quantitatively small and positive, meaning we would expect the employment gap to improve by 0.06 percentage points, if we just account for differences in exposure to permanent employment. This small positive number reflects that without a change in hiring or firing policies, Black workers should be less affected by a contraction that leads to lower employment for white workers because they are employed at lower rates overall. In order for there to be a negative composition effect, we would need the change in employment for white workers at large firms to be significantly more negative than the change at small firms. Large firms do contract employment slightly more than small firms in the model, but it is not enough to lead to negative composition effects for Black workers because the absolute difference in initial employment rates are so

Table 8: Decomposition of steady state comparison

<i>Changes: low - high productivity</i>					
	Baseline	No matching distortion	No statistical	No taste	
Employment gap	-1.37	-0.71	-0.32	-0.83	
Large	-1.43	-0.73	-0.27	-0.96	
Small	0.06	0.02	-0.05	0.12	
Composition effects	0.04	0.04	-0.04	0.04	
Large, permanent	-0.04	0.03	-0.09	0.01	
Large, temporary	-0.01	-0.01	0.00	-0.01	
Small, permanent	0.09	0.02	0.05	0.05	
Small, temporary	0.00	-0.01	0.00	-0.01	
Policy effects	-1.44	-0.77	-0.29	-0.90	
Large, permanent	-1.40	-0.77	-0.17	-0.97	
Large, temporary	-0.01	-0.01	0.00	0.00	
Small, permanent	-0.03	0.02	-0.10	0.08	
Small, temporary	0.00	0.00	-0.01	0.00	

This table shows the decomposition of the change in the racial employment gap between steady states defined in equation 28. The first column reports the baseline calibration and the subsequent columns remove each channel for racial disparities.

much larger.

The composition effects of temporary employment are quantitatively small and negative because firms reduce temporary employment when productivity decreases, and Black workers are over-represented in temporary employment. The decrease in temporary employment happens because the decrease in labor demand leads to an increase in the job-filling rate, $q(\theta)$. This allows firms to substitute more towards a high selectivity strategy: they post more vacancies and become more selective about the marginal worker hired. As in the case of permanent employment, Black workers are somewhat less exposed to these changes because their overall employment is lower, but they are also over-represented in temporary employment relative to permanent employment so the overall effect is negative. The degree of statistical discrimination is influential for this. The small negative effect goes to zero if we turn off statistical discrimination, though this also leads the initial employment gap to disappear as well.

The overall worsening of the employment gap in the model happens because changes in

hiring policy lead Black workers' over-representation at large firms to decrease and under-representation at small firms to worsen. The change in hiring policy in the model can be understood through the cost minimization solution in equation 24, which acts as a free entry condition. A decrease in productivity leads to lower labor demand, which leads $c_v(z)/q(\theta)$ to fall. This has heterogeneous effects on hiring policy due to size differences and racial differences by size. First, because $c_v(L) < c_v(S)$, the curvature of the signal distribution determines the relative impact on hiring by firm size. Figure 3 plots the condition from equation 24 separately by race and firm size under the baseline calibration (high a) and the counterfactual low productivity state (low a), using the relationship between x_{Wz}^* and x_{Bz}^* implied by equations 25 and 26. The x-axes convert the hiring decision rule, x_{gz}^* into the share of matches hired and all four plots use the same x-axis range. Comparing the intersection of the solid orange line with the two dashed lines in panel (a) and panel (c), the direct effect of the same decrease in θ has a bigger impact on small firms, because they are less selective initially and the curvature of the distribution is such that they become more selective. Large firms reduce the share of white workers hired by roughly 0.6 percentage point, whereas small firms reduce this share by 1.3 percentage point.

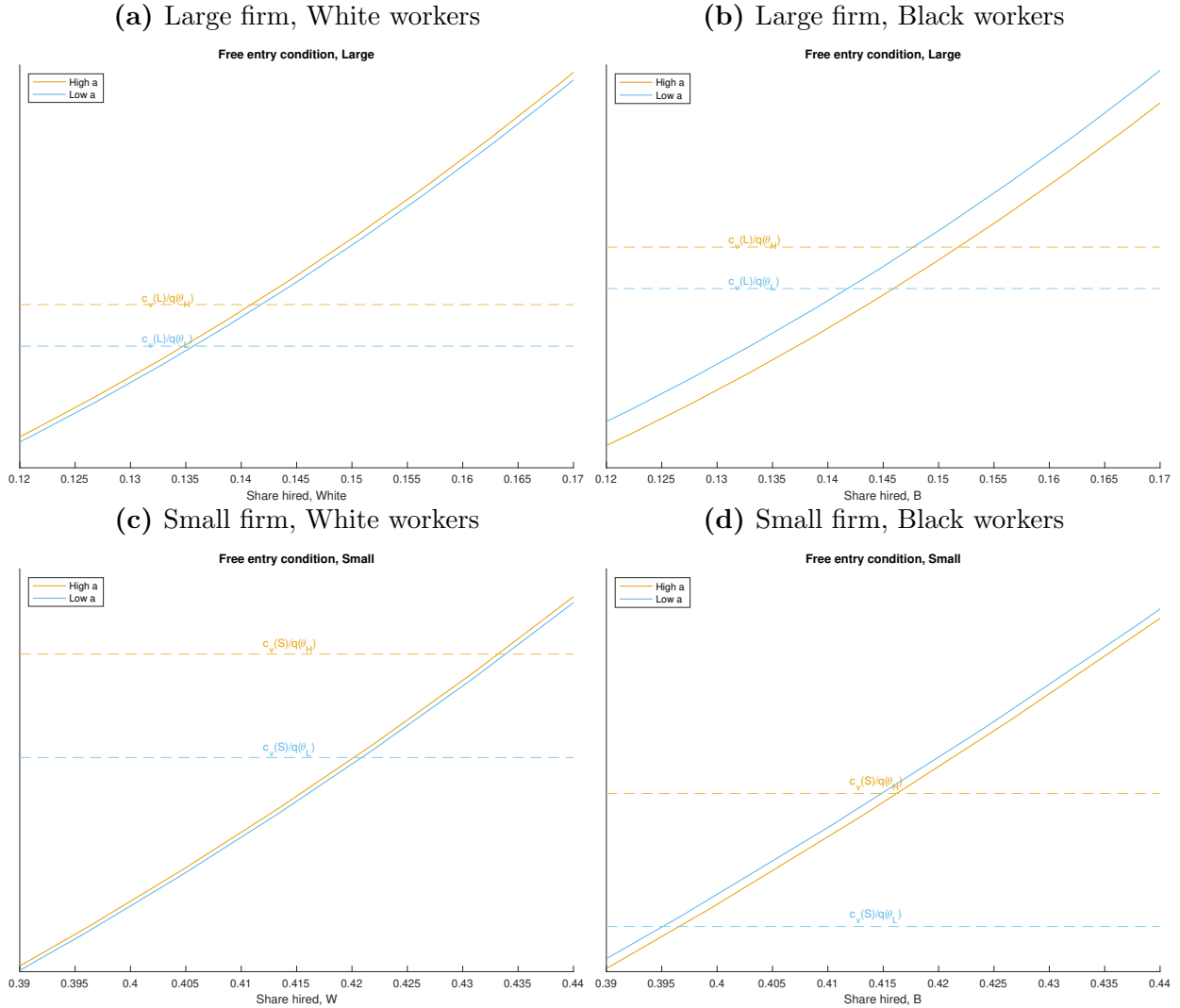
The direct effect for Black workers will differ for two reasons. First, firms had a different threshold rule to start, so the magnitude of the decrease will depend on the curvature of the signal distribution at that point. Second, the lower signal quality means that a proportional change in in the threshold rule will lead to a more than proportional change in the share of matches hired if firms are being sufficiently selective, or a less than proportional change if they are relatively lenient. The direct effect for Black workers at large firms is comparable to white workers (0.59 ppt vs. 0.61) because these two channels are working against one another. If Black workers faced the same signal quality as white workers, the reduction would be 0.5 ppt. It is larger because the lower signal quality amplifies this change. For Black workers at small firms, the direct effect is substantially larger at 2.0 percentage points. Without the difference in signal quality, the change in the threshold alone would lead this change to be 1.4 percentage point. Thus at small firms, both effects are leading to a worsening for Black workers.

The feedback effect occurs because the free entry condition also shifts due to the change in workers' outside options, Ω_g , which arises due to the change in selectivity coming from the direct effects. Similar to the intuition above, even though the change in hiring rules is larger for Black workers at small firms, they are less exposed to this both because they were hired at lower rates already and because the distortion in matching shifts relatively more applicants towards large firms. Thus, the outside option of white workers worsens more than Black workers, leading firms to become relatively less selective about the white workers they hire and more selective about Black workers, as demonstrated by the shift from the orange solid curves to the blue solid curves in Figure 3. This leads firms to adjust their hiring by even more for Black workers, particularly at large firms, which face less binding channels of racial discrimination.

The additional columns in Table 8 report the counterfactual results when each form of racial disparities is turned off. Removing statistical discrimination has the largest impact because the policy effects described above are not amplified by differences in noise. The initial racial gap in employment is slightly positive, as reported in Table 6, so this decrease effectively closes the positive racial employment gap. The composition effects are negative because large firms contract by more, Black workers are more exposed to large firms, and the effect of having less employment overall is not present since Black workers actually have slightly higher employment initially. Without statistical discrimination, the composition effects become relatively more important than the policy effects for understanding why large firms contribute more to the decrease in employment. Interestingly, the gap worsens by roughly half as much without the matching distortion. This suggests that distortions in the matching process can lead to a greater sensitivity to aggregate conditions.

The model-implied policy effects are sensitive to the calibration, particularly parameters that affect the cutoff rules, x_{gz}^* and the shape of the match quality distribution. Appendix table B.3 shows how the results vary with the shape parameter, γ , and the target for the share of matches that are hired. As the curvature increases, more of the policy response comes from small firms. Similarly, as the average selectivity decreases (going from 20% to 40%), the policy response shifts to be driven by small firms. Because the policy effects are

Figure 3: Relative selectivity of hiring



driven by the adjustment in relative wages, they are also sensitive to the assumption that firms are allowed to pay workers different wages for the same productivity. If I remove this assumption, small firms contribute relatively more to the total decrease in the employment gap. Table B.5 reports these results and the additional scenario in which only small firms are allowed to pay different wages. In that case, large firms contribute relatively more to the change in the employment gap than in the case with no wage discrimination, but not as much as in the model with full wage discrimination.

More generally, they give a nice framework for thinking about what forces would produce

the pattern in the data that large firms contribute more to the worsening of the employment gap. If Black workers are disproportionately matched to large firms due to differences in networks that lead to coracial hiring (larger $\lambda_{Bz}/(1 - \lambda_{Bz})$), then small changes in marginal hiring decisions will be amplified. For example, if discrimination rises in slack labor markets, as suggested by [Boulware & Kuttner \(2019\)](#), then even if large firms are not the predominant discriminating firms, their behavior could be amplified by distorted matching rates. Meanwhile, since Black workers are less likely to work for small firms at baseline, even if they do discriminate more in slack labor markets, the total effect on Black employment at small firms will be attenuated by the positive contribution of composition effects.

Temporary employment plays a limited role in this model: these workers represent type I errors in hiring decisions. In a more general specification, large firms would contribute more to the worsening employment gap if Black workers are overrepresented in temporary employment and large firms cut temporary employment more than permanent employment.

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. Rather than assuming one form of racial disparities, I allow for three channels and use data to tease out the relative magnitudes of each. I find that statistical discrimination is important for generating the employment gap in the data, whereas distortions in matching rates and taste-based discrimination are relatively more important for generating the sorting of Black workers towards large firms.

A permanent decrease in productivity leads to a steady state with a wider racial employment gap because firms become more selective about hiring, which disproportionately affects Black workers. 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. Distortions in matching rates towards incumbent employment can amplify other forms of discrimination. Statistical discrimination is especially important for the source of the employment gap in the model and the reason that large firms have an outsized role in the decrease in employment in the counterfactual low productivity steady state.

In both the data and the model, composition effects played a limited role in excess decrease in Black employment in a slack labor market. In the data, large firms contributed more than their proportional share to a variance decomposition of Black employment. In the model, composition effects made a small positive contribution to the change in the employment gap between steady states.

The model allows me to attribute the remaining change to policy effects, caused by changes in firms' hiring policies in response to lower aggregate productivity. The magnitude of these effects varies with the calibration, but they are informative about the types of conditions that would lead large firms to drive the change in employment for Black workers. First, large firms are especially responsive when wages are flexible. If both large and small firms can discriminate on the basis of wages, then changes in small-firm hiring that makes white workers worse off gives large firms less incentive to hire Black workers. Second, large firms are more responsive in cases where firms are very selective about which workers to hire. This is because statistical discrimination is more salient when firms are being more selective.

The spillover effects between small and large firms suggest that regulating only the biggest players will miss some of these economy-wide effects. They also suggest that although 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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Supplemental 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; management-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.

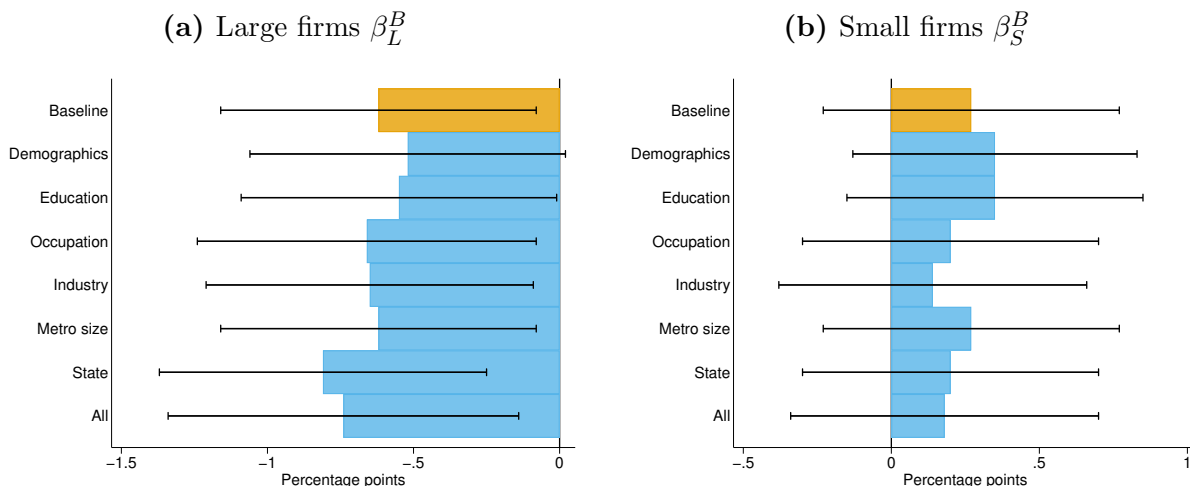
A.2. Alternative specification

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,

$$E_{ijt} = \alpha_{ij} + \beta_j UR_t + \beta_j^B \text{Black} \times UR_t + \Gamma X_{it} \times UR_t + \epsilon_{ijt}. \quad (\text{A.1})$$

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



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)	(2)	(3)	(4)	(5)
	All	Large	Small	Government	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 \times 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)	(2)	(3)	(4)	(5)
	All	Large	Small	Government	Self
UR	-1.63	-1.41	-0.34	0.12	-0.06
	(0.30)	(0.18)	(0.14)	(0.08)	(0.09)
Black \times 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)	(2)	(3)	(4)	(5)
	All	Large	Small	Government	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 \times 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)	(2)	(3)	(4)	(5)
	All	Large	Small	Government	Self
UR	-1.35	-1.18	-0.26	-0.07	0.10
	(0.30)	(0.20)	(0.14)	(0.11)	(0.07)
Black \times 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)	(2)	(3)	(4)	(5)	(6)
	All	Large	Small	All	Large	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 \times 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)	(2)	(3)	(4)	(5)	(6)
	All	Large	Small	All	Large	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 \times 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)	(2)	(3)	(4)	(5)	(6)
	All	Large	Small	All	Large	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 \times 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)	(2)	(3)	(4)	(5)	(6)
	All	Large	Small	All	Large	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 \times 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)	(2)	(3)	(4)	(5)	(6)
	All	Large	Small	All	Large	Small
Black	0.38 (0.07)	0.46 (0.09)	0.63 (0.17)	0.38 (0.05)	0.49 (0.06)	0.58 (0.12)
UR	0.05 (0.04)	0.00 (0.04)	0.17 (0.07)	0.21 (0.03)	0.21 (0.03)	0.41 (0.05)
Black \times UR	0.06 (0.07)	0.04 (0.09)	0.01 (0.16)	0.07 (0.05)	0.08 (0.07)	0.01 (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)	(2)	(3)	(4)	(5)	(6)
	All	Large	Small	All	Large	Small
Black	0.14 (0.06)	0.32 (0.08)	0.30 (0.14)	0.32 (0.04)	0.40 (0.05)	0.44 (0.09)
UR	-0.11 (0.05)	-0.12 (0.05)	-0.18 (0.06)	0.14 (0.03)	0.14 (0.03)	0.17 (0.03)
Black \times UR	-0.06 (0.05)	-0.18 (0.07)	0.10 (0.13)	-0.07 (0.03)	-0.06 (0.05)	-0.07 (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

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

where $\tilde{n}_g = (1 - \delta)n_g$ is the number of non-separated workers from group g from the previous period and $h_g = \lambda_{gz} v q(\theta_t)(1 - F(x_g|p_{gz}))$ 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 as²⁰

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

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

²⁰The 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.

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

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

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

Using the bargaining rules defined in equations (16) and (17),

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

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

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

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

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

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. Alternative calibrations

I report sensitivity to alternative calibrations. Table B.1 reports parameter estimates for the baseline model and four alternative calibrations: setting shape parameter γ at 2 or 4 instead of baseline 3, and setting the target for the share of matches hired to 30% or 40% instead of 20%. Table B.2 reports the model moments. Tables B.3 and B.4 report the results of the counterfactual decomposition.

Table B.1: Fitted parameters across alternative calibrations

Parameter	Meaning	Baseline	$\gamma = 2$	$\gamma=4$	30% target	40% target
ζ	Matching scale	0.642	0.640	0.641	0.427	0.318
μ	Number firms/worker	0.009	0.009	0.009	0.009	0.008
b	Flow value unemp	0.979	0.982	0.970	0.962	0.934
ϕ	Bargaining power	0.360	0.341	0.405	0.436	0.551
δ	Exog. separation	0.024	0.026	0.022	0.022	0.020
$c_v(L)$	Vacancy cost	0.012	0.005	0.021	0.022	0.033
$c_v(S)$	Vacancy cost	0.196	0.291	0.174	0.183	0.159
$\frac{z_L}{z_S}$	Relative productivity	4.067	4.053	4.056	4.025	3.993
λ	Matching distortion	0.630	0.671	0.634	0.635	0.651
Δp_L	Signal gap, large	0.186	0.068	0.162	0.190	0.212
Δp_S	Signal gap, small	0.285	0.211	0.240	0.321	0.358
$\Delta \chi_L$	Taste penalty, large	0.003	0.010	0.003	0.010	0.020
$\Delta \chi_S$	Taste penalty, small	0.013	0.030	0.012	0.029	0.053

Table B.2: Moments across alternative calibrations

(a) Aggregate moments

Moment	Data	Baseline	$\gamma=2$	$\gamma=4$	30% target	40% target
Employment share						
Large	0.64	0.64	0.64	0.64	0.64	0.64
Job-finding rate, ppt						
Large	6.45	6.42	6.39	6.45	6.45	6.52
Small	4.78	4.83	4.85	4.78	4.78	4.63
Separation rate, ppt	3.17	3.16	3.22	3.17	3.17	3.19
Large	3.05	2.81	2.85	2.83	2.84	2.90
Small	4.07	3.81	3.88	3.78	3.78	3.70
External						
Hired share matches	0.20	0.20	0.20	0.20	0.30	0.40
Market tightness	0.72	0.72	0.72	0.72	0.72	0.72
Outside option	1.00	1.00	1.00	1.00	1.00	1.00
Ratio b to avg prod	0.73	0.73	0.73	0.73	0.73	0.73
Vacancy yield	1.30	0.19	0.19	0.18	0.18	0.18
Vacancy yield, Large	0.70	0.13	0.11	0.13	0.14	0.15

(b) Racial gap moments

Moment	Data	Baseline	$\gamma=2$	$\gamma=4$	30% target	40% target
Employment, ppt (B-W)						
Empl rate	-4.08	-4.09	-4.03	-4.08	-4.08	-4.03
Large-firm share	6.20	6.19	6.20	6.20	6.20	6.21
Job-finding, ppt (B-W)						
Large	0.10	-0.04	-0.61	0.00	-0.01	0.14
Small	-2.23	-1.27	-1.71	-1.24	-1.23	-1.14
Separation, ppt (B-W)						
Large	0.40	0.38	0.09	0.40	0.39	0.46
Small	0.51	0.49	0.01	0.51	0.51	0.54
Contact gap	0.36	0.13	0.12	0.14	0.14	0.15
Large firms	0.09	0.09	0.09	0.09	0.09	0.09

The figures in bold represent untargeted moments. The data moments are all calculated in the SIPP except for the external moments and contact gaps.

Table B.3: Decomposition of steady state comparison with alternative match quality shape parameters

<i>Changes: low - high productivity</i>				
	Baseline ($\gamma=3$)	$\gamma=2$	$\gamma=4$	
Employment gap	-1.37	-4.19	-0.73	
Large	-1.43	-5.57	-0.64	
Small	0.06	1.37	-0.08	
Composition effects	0.04	0.12	0.02	
Large, permanent	-0.04	-0.02	-0.03	
Large, temporary	-0.01	0.00	-0.01	
Small, permanent	0.09	0.14	0.07	
Small, temporary	0.00	0.00	0.00	
Policy effects	-1.44	-4.35	-0.76	
Large, permanent	-1.40	-5.59	-0.60	
Large, temporary	-0.01	-0.02	-0.01	
Small, permanent	-0.03	1.25	-0.15	
Small, temporary	0.00	0.01	-0.01	

This table shows the decomposition of the change in the racial employment gap between steady states defined in equation 28. The first column reports the baseline calibration and the subsequent columns report results for alternative calibrations for the shape of the match quality distribution, γ .

Table B.4: Decomposition of steady state comparison with alternative selectivity targets

<i>Changes: low - high productivity</i>			
	Baseline (share hired = 20%)	30%	40%
Employment gap	-1.37	-0.92	-0.59
Large	-1.43	-0.61	-0.07
Small	0.06	-0.32	-0.52
Composition effects	0.04	0.01	-0.01
Large, permanent	-0.04	-0.03	-0.03
Large, temporary	-0.01	-0.01	-0.01
Small, permanent	0.09	0.05	0.02
Small, temporary	0.00	0.00	0.00
Policy effects	-1.44	-0.95	-0.58
Large, permanent	-1.40	-0.57	-0.04
Large, temporary	-0.01	-0.01	0.00
Small, permanent	-0.03	-0.36	-0.52
Small, temporary	0.00	-0.01	-0.02

This table shows the decomposition of the change in the racial employment gap between steady states defined in equation 28. The first column reports the baseline calibration and the subsequent columns report results for alternative calibrations that vary the target for the average share of matches that are hired.

Table B.5: Decomposition of steady state comparison without wage discrimination

<i>Changes: low - high productivity</i>				
	Baseline	No wage discrimination	Only wage disc. at small firms	
Employment gap	-1.37	-0.65	-0.73	
Large	-1.43	-0.33	-0.39	
Small	0.06	-0.33	-0.34	
Composition effects	0.04	0.03	0.03	
Large, permanent	-0.04	-0.05	-0.04	
Large, temporary	-0.01	0.00	-0.01	
Small, permanent	0.09	0.09	0.08	
Small, temporary	0.00	0.00	0.00	
Policy effects	-1.44	-0.70	-0.77	
Large, permanent	-1.40	-0.28	-0.35	
Large, temporary	-0.01	0.00	0.00	
Small, permanent	-0.03	-0.41	-0.41	
Small, temporary	0.00	-0.01	-0.01	

This table shows the decomposition of the change in the racial employment gap between steady states defined in equation 28. The first column reports the baseline calibration and the subsequent columns report results when I remove firm's ability to pay different wages for workers with the same productivity. The first scenario removes all wage discrimination. The second removes wage discrimination just at large firms.