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 cycle exposure factors. This paper introduces a new channel to explain the excess sensitivity of Black employment: employer heterogeneity in hiring. There are persistent differences in the job-finding and separation rates of Black and white workers across firms of different sizes. Black workers face higher separation rates and lower job-finding rates on average, with more extreme disparities at *small* firms. Meanwhile, when the labor market is weak, the job-finding rate falls more for Black workers, with the biggest drop coming from *large* firms. The second half of the paper introduces a search model with employer size-specific information frictions that captures these patterns. The abundance of available workers during downturns encourages firms to be more selective about the workers they hire, leading to worse hiring outcomes for minority workers at all firms. This selection effect can produce larger changes in hiring rates for the disadvantaged workers at firms with better screening technology, because these firms are able to capture a higher share of the matching market and they are more susceptible to general equilibrium effects.

JEL: E24, J63, J71, M51

Keywords: Racial employment gap, firm heterogeneity, worker heterogeneity

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1. Introduction

The Black population in the U.S. faces persistently lower rates of employment than the white population. Additionally, Black employment responds more to macroeconomic conditions, rising more during expansions but also falling more during contractions. For example, over the peak to trough of the Great Recession, the Black employment rate fell by 4.5 percentage points whereas the white employment rate fell by 3.2 percentage points. Understanding the 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 information frictions in explaining the higher aggregate employment volatility for Black workers. The empirical section shows that Black workers face especially higher separation rates and lower job-finding rates at small firms, consistent with the fact that Black workers are more likely to be employed by large firms. Meanwhile, when the economy contracts, the reduction in job-finding for Black workers at large firms is the strongest driver of the worsening employment gap. Motivated by existing micro-level research, the second half of the paper builds a model in which heterogeneous workers and firms meet in a labor market with information frictions. Minority workers face more severe information frictions, particularly at small firms, which generates a lower minority employment rate and a higher propensity for minority workers to be employed by large firms. The model is also consistent with the pattern that large firms contribute most to the worsening employment gap when the economy is weak.

In the empirical section, I document differences in employer-type specific transition rates by race and how they vary with aggregate conditions. I use micro-level data to adjust for differences in industry composition, geography, and other factors. Over my sample period of 1996 to 2012, the Black separation rate was 0.09 percentage point higher on average than the white separation rate, after controlling for worker and job characteristics. This headline number masks considerable heterogeneity across employer types, with separations at large firms roughly twice as high and separations at small firms three times as high.

Meanwhile, the rate at which Black workers moved from nonemployment to employment was 0.76 percentage point lower than for white workers, with -0.59 percentage point of that gap coming from small firms and only -0.07 percentage point from large firms.

Next, I examine how these patterns change with aggregate conditions in the economy. When the headline unemployment rate is high, separations increase and job-finding decreases. For Black workers, the drop in the job-finding rate at large firms is especially large, falling by nearly twice as much as the job-finding rate for white workers. Given the already high separation rate for Black workers, the decrease in job-finding is especially important, contributing to the lower overall employment rate during these periods.

In Section 4, I develop a model to study how information frictions in the hiring process across firms contribute to the patterns in the data that Black workers are more likely to work for large firms and that large firms contribute more to the worsening of the the job-finding gap when the labor market is weak. I start with a canonical random search model and introduce three main ingredients: endogenous firm size, uncertain worker productivity, and differences in screening technology across worker groups and firm sizes. 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. Alternatively, if they choose a low selectivity strategy, they pay lower search costs but higher turnover means they pay more wages to workers who end up separating quickly.

I assume that small firms have worse screening technology than large firms and that all firms receive noisier signals about minority worker productivity. The first assumption implies that the benefit of screening workers is lower for small firms and they will choose a lower selectivity strategy than large firms. This produces higher turnover rates at small firms. The second assumption generates the lower employment rate for minority workers. More noise in the signal for minority worker productivity means firms identify fewer minority workers who satisfy their hiring criteria, leading to negative job-finding gaps at both types of firms. The combination of both assumptions generates the higher share of minority employment at large firms and more severe job-finding gaps at small firms.

The model predicts that the racial employment gap can worsen with lower aggregate productivity. Decreased demand for labor leads to a decrease in market tightness, allowing firms to attract more applicants per unit of search intensity. Thus, the relative cost of the high selectivity strategy decreases, which negatively affects minority workers. The effect is more severe at large firms because their more efficient screening technology enables them to capture more of the market for matches and makes them more sensitive to general equilibrium effects on wages.

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; to name a few). Most of these papers focus on the stylized fact that the Black unemployment rate is roughly double the white unemployment rate and this ratio is constant over the business cycle. They conclude that this pattern is maintained because Black workers are last hired and first fired in response to shocks. My finding that the job-finding margin is the most gap for Black workers during downturns is consistent with recent evidence by Forsythe & Wu (2021) and Kuhn & Chancí (2021). Another related area of research is considering the effects of monetary policy on racial inequality (see Bartscher *et al.*, 2021; Lee *et al.*, 2022; Bergman *et al.*, 2020; Thorbecke, 2001; Carpenter & Rodgers III, 2004; Zavodny & Zha, 2000). This literature demonstrates the policy interest of understanding how racial differences evolve over the business cycle. My paper contributes to this literature by introducing the role of employer heterogeneity, which is interesting on its own for understanding how shocks permeate through the economy, but also could have important implications for economic policies that interact with the firm size distribution.

Second, there is a large micro literature documenting racial disparities and discrimination in the labor market (see Lang & Lehmann (2012) for an overview). The fact that Black workers are more likely to be employed by large firms was documented by Holzer (1998) and has more recently been emphasized by Miller (2017) and Miller & Schmutte (2021). Morgan

& Várdy (2009) shows that if firms are sufficiently selective, then differences in "discourse systems" that make it harder for firms to evaluate minority workers will lead to underrepresentation of minorities. Miller & Schmutte (2021) uses this framework to show that differences in referral networks can lead minority workers to disproportionately sort to large firms (Okafor (2022) highlights a similar mechanism without firm size). My paper builds on this literature by evaluating the role of this type of information friction with endogenous firm size and endogenous wages. My model could be easily adapted to study disparities along other dimensions besides race, whenever one group faces stronger information frictions due to differences in professional networks or other reasons.

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), and shown that information frictions are important in this context (Baydur, 2017). My paper extends these findings to show that firm heterogeneity and information frictions are important to understanding both the persistence of racial employment gaps and their relationship to aggregate economic conditions.

Outline

The rest of the paper proceeds as follows. Section 2 describes the data and background empirical facts. Section 3 provides empirical evidence of job flows by race and firm size. Section 4 introduces the model and describes the channels through which employer composition affects employment fluctuations by race. Section 5 describes the model calibration and results. Section 6 provides counterfactuals. Section 7 concludes.

2. Background Empirical Facts

2.1. Data

Survey of Income and Program Participation (SIPP)

My primary data source is 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. Relative to the Current Population Survey (CPS), which is commonly used to study employment transitions, the SIPP is a smaller survey and is designed to be representative at the national level but not the state level. The main advantage of the SIPP is that it asks workers about the size of their employer, which can be matched to the employment transitions data. I define large firms as those with 100 employees or more, as firms above that threshold are not further disaggregated during my sample period. By this definition, roughly 60% of privately employment is at large firms over the course of my sample. I primarily use this dataset for studying worker transitions between employment states.

The SIPP is a rotating panel that interviews households every four months for approximately 3-4 years. Each panel has a nationally representative sample of households, leading to a sample size of about 80,000 to 100,000 adults per panel. Interviews are staggered such that one quarter of the sample is interviewed during each month. In each interview, household members are asked about their weekly labor force status over the previous 18 weeks. Employed workers are asked to provide details about up to two jobs per interview period, including start and end date, firm size, occupation, industry, and type of employer (e.g. private employer or government). They are also asked about similar details for up to two businesses they own. Both jobs and businesses are assigned an identifier so that they can be tracked across interview waves.

I will be using data from the 1996, 2001, 2004, and 2008 panels.[1] For most of my

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

analysis I will be focusing on individuals aged 20 or older who self-identify as non-Hispanic white or Black. This gives me a sample of about 286,000 individuals who I observe for an average of 22 months.

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 week corresponding to the BLS convention, as described by Fujita *et al.* (2007). I first assign workers as either employed or non-employed (either unemployed or out of labor force). I am choosing to focus on non-employment rather than unemployment because I want to focus on differences between employers rather than differences in labor force participation behavior over the business cycle. To address the problem of seam bias, whereby respondents are more likely to report employment transitions over the months between survey waves, I exclude the first month of each four-month panel (Moore, 2008).

For workers who are employed, I use the job and business history information, particularly start and end dates, to match their employer characteristics to their 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. For workers who are simultaneously employed by two jobs, I select the job that has higher reported hours, with longer tenure used 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 who report being employed to their employer type. This classification is not 100% because some workers have more than two employers over the four month survey period so I only observe the two that they choose to describe in the interview, or there may be inconsistencies in the start/end dates.

Current Population Study (CPS)

For additional motivation, I use the CPS to show aggregate employment patterns by race. As with the SIPP, I include all individuals aged 20 and older.

As a validation for my measures of firm size in the SIPP, I use the March Annual Social and Economic Supplement (ASEC), which provides an annual snapshot of employment and employer composition, but lacks the detailed transition dynamics from the SIPP. The survey asks questions about all household members' current employment status, as well as more detailed questions about the main job they held in the previous year. This includes industry, occupation, earnings, and notably, firm size. The firm size variable is also more detailed than the variable in the SIPP, allowing me to present sorting patterns with alternative thresholds. My sample covers individuals aged 18-65 for calendar years 1987-2019. The sample size varies from about 75k to 115k adults per year.

2.2. Employment over the Business Cycle

The Black employment-to-population ratio is consistently lower than the white employment-to-population ratio. The solid orange line in Panel (a) of Figure 1 plots the level difference in these ratios for the Black relative to the white population. Additionally, the gap exhibits strong business cycle sensitivity, tending to become more negative around the shaded NBER recession periods. The correlation with the headline unemployment rate is -0.8, meaning that when the unemployment rate is higher, the Black employment rate tends to fall by more.

Some of the difference in employment rates can be explained by differences in demographics, occupation, industry, or geography, but the cyclical pattern cannot. The dashed blue line in Figure 1 shows the conditional gap, which is the portion of the gap that cannot be explained by observable worker characteristics within each month.[2] To estimate this conditional gap, I use a Oxaca-Blinder decomposition within each month, described in Appendix A.2. If the Black employment rate tended to fall more during downturns because Black workers were more likely to work for volatile industries, for example, then the cyclical pattern should disappear after controlling for time-specific industry effects. As seen in Figure 1, this is not the case. The conditional gap has a lower absolute value mean and the variance is lower, but the correlation with the business cycle is still high. For example, the correlation between the conditional employment gap and the headline unemployment rate is

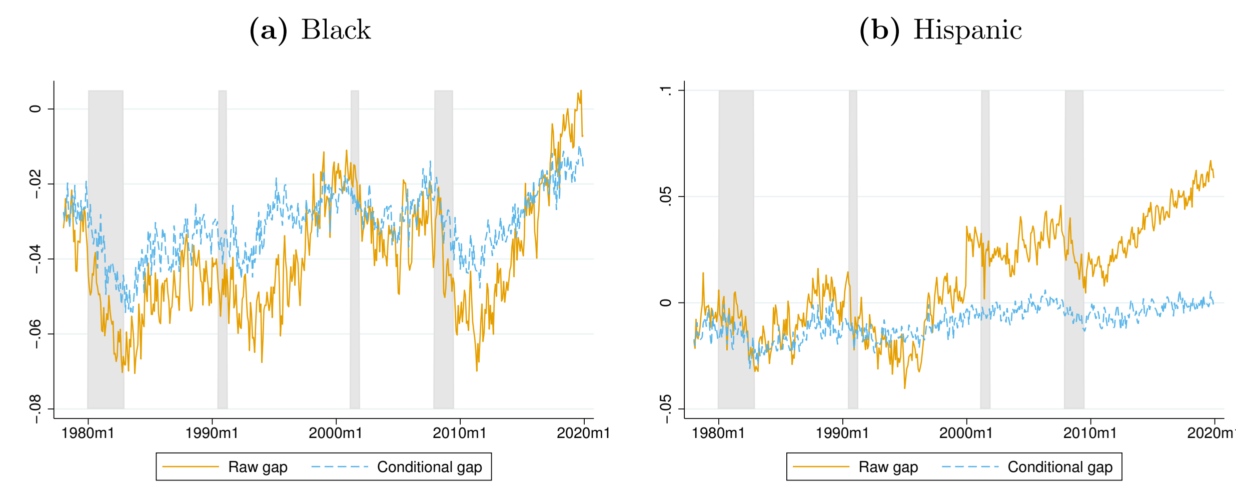
[2] The controls are an age quadratic by gender, marital status by gender, occupation, industry, state, and metro area size.

-0.81.

For comparison, Panel (b) shows that the Hispanic employment rate has exceeded the white employment rate over the last couple of decades, as seen in the solid blue line. However, it is still slightly lower than would be predicted by worker characteristics, and is countercyclical, with a correlation of -0.5 with the headline unemployment rate.

Appendix Figure 9 reports the raw and conditional employment gaps separately by gender. Although the raw gaps exhibit substantially different patterns by gender, the conditional gaps are similar. Appendix Table 13 summarizes these gaps and their correlations with the unemployment rate. The countercyclical employment gap for Black workers also holds when measured in logs rather than levels. Appendix Figures 10 and 11 show the employment gaps across and within genders in logs rather than levels, and Table 14 summarizes. Appendix A.2 provides more details and discussion about each of these exercises.

Figure 1: Employment-to-population ratio relative to white

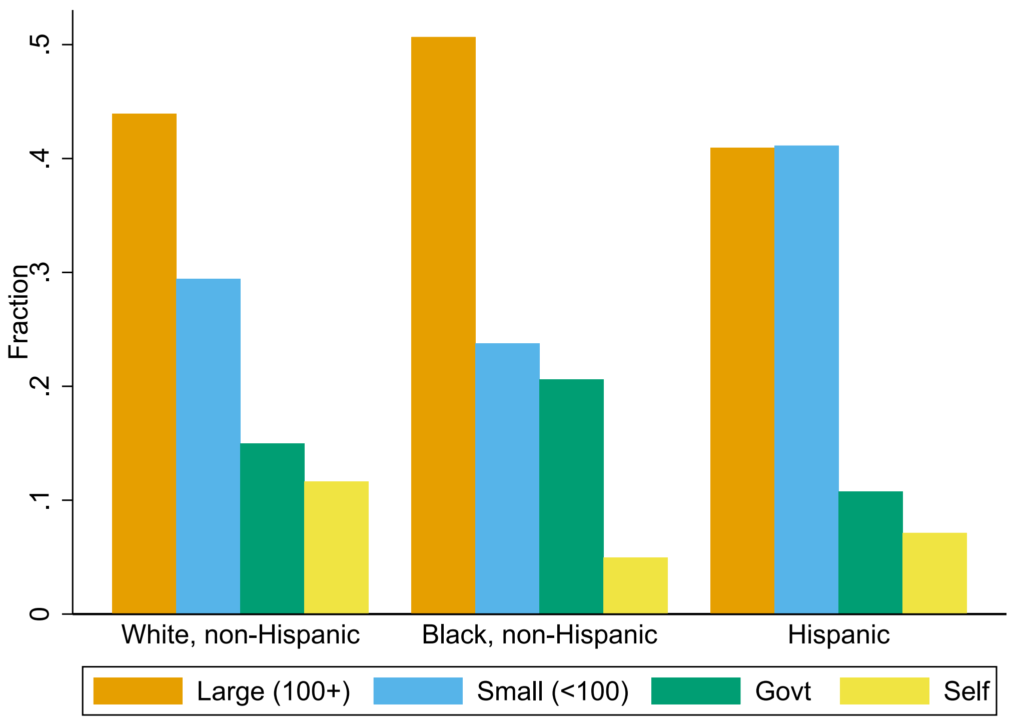


Source: CPS.
The solid (Raw gap) line plots the employment-to-population ratio for the Black and Hispanic populations relative to the white population. The mean is -3.9 percentage points and standard deviation 1.6. The dashed (Conditional gap) line plots the within-month employment gap, conditional on an age quadratic by gender, marital status by gender, occupation, industry, state, and metro area size. The mean is -3.1 percentage points and standard deviation 0.9.

2.3. Heterogeneity in Employer Composition

To illustrate the differences in employer composition, I plot the average distribution of employers for non-Hispanic white and Black and Hispanic employed workers over 1988 to 2019. Figure 2 shows that for both white and Black workers, large firms make up the majority of employers, but this difference is even larger for Black employees. Meanwhile, Hispanic workers are overrepresented in small firms.

Figure 2: Employer composition by race and ethnicity

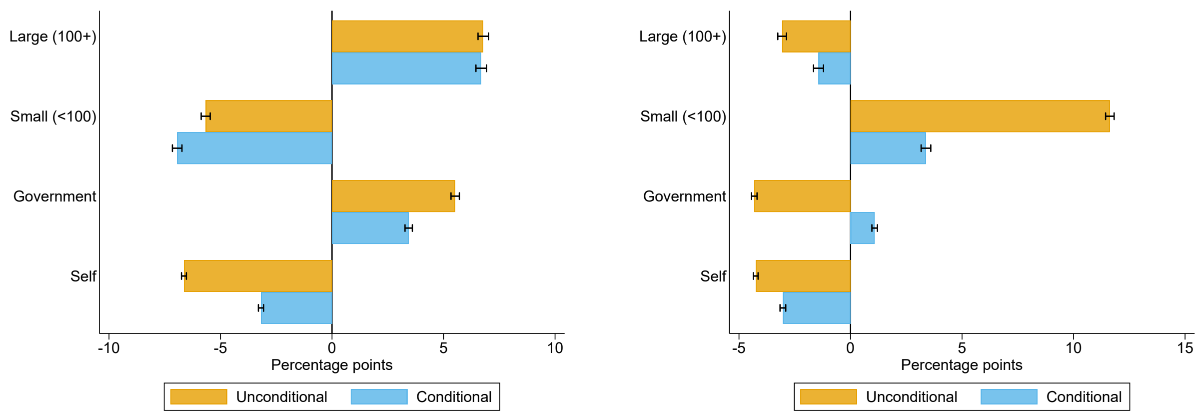


Source: ASEC supplement to the CPS
Bars represent the average annual fraction of workers who report each employer type as their primary job over the prior year. The sample covers the adult population aged 18-65 from 1988-2020.

To evaluate how much of this difference in employer composition is attributable to differences in industry, occupation, location, and other observable features, I use a linear probability model and regress an indicator for working for each type of employer on a number of observable worker characteristics and a race/ethnicity-specific dummy variable. Figure 3 shows that while differences in government and self employment are somewhat explained by differences in observable variables, the gap in firm size is not. Appendix Table 15 reports similar patterns using a higher threshold and with data from the SIPP.

Figure 3: Employment composition relative to white

(a) Black **(b)** Hispanic



Source: CPS.
Conditional estimates control for age, age-squared and education by gender, occupation, industry, state, and metro area size.

Meanwhile, the massive gap in the likelihood of working for small firms for Hispanic workers is largely explained by differences in industry and other characteristics. Due to these different patterns in the employment gap over time and employer composition, I will limit my focus to Black and white non-Hispanic workers, though there is clearly more heterogeneity to be explored in future work by examining other racial and ethnic groups. The limited sample size of the SIPP and limited detail about race and ethnicity also make it difficult to expand further to other minority groups with precision.

3. Empirical Evidence

The previous section showed that Black employment is more cyclically sensitive than white employment and that Black workers are more likely to work for large firms. This section will show how differences in job-finding and separation rates vary by race and firm size both on average and over the business cycle.

3.1. Transition rates by race

Before exploring heterogeneity by firm size, I start by documenting patterns in employment transitions by race in the SIPP and how they vary with aggregate conditions in the economy. In particular, I define high UR months as those in which the difference between the headline unemployment rate and its time-varying noncyclical rate of unemployment is in the top third of monthly observations.[3] Of the 181 months in my sample, 55 are considered high UR by this measure. I choose this binary measure as the baseline specification rather than the continuous gap because it maps better to the steady state comparison in the model. Additional results using continuous measures are reported in Appendix B. I choose to focus on the top third rather than the top half to isolate more severe periods.

I start with a linear probability model, with the following specification,

$$s_{it}^{N} = \alpha + \alpha^{B}\text{Black}_i + \beta\text{HighUR}_t + \beta^{B}\text{Black} \times \text{HighUR} + \Gamma X_{it} + \epsilon_{it}, \tag{1}$$

where s_{it}^{N} is an indicator equal to 1 if individual i is nonemployed in month t conditional on being employed in month $t-1$; Black_i is a racial dummy variable; HighUR_t is an indicator for whether month t is in the top tercile of unemployment gap deviations from trend; and X_{it} is a vector of worker and lagged job characteristics. Worker characteristics are age, age-squared, and marital status, all interacted with gender; education; geographic region; and an indicator for large metro area. Job characteristics are industry; occupation; and length of employment spell in years. I also include fixed effects for calendar month. Given that the variation is at the month level, I cluster standard errors by time.

The point estimates for the main coefficients of interest are reported in Panel (a) of Table 1. Starting in column 1, Black workers are 0.09 percentage points more likely to separate from employment than white workers in the reference periods. Moving to columns (2)-(3), this gap is somewhat smaller when we consider men and women separately, but still positive. In high unemployment months, all workers are about 0.05 percentage points more likely to

[3]The noncyclical rate of unemployment replaced the natural rate of unemployment, published by the Congressional Budget Office. I construct the thresholds using the full sample of data from 1949 to 2023.

separate from employment, with this effect being driven by men. Finally, separations for Black workers do not rise disproportionately in the SIPP data during high unemployment months.

Next, I document the patterns for job-finding rates, where I use the model,

$$f_{it} = \alpha + \alpha^B \text{Black}_i + \beta \text{HighUR}_t + \beta^B \text{Black} \times \text{HighUR} + \Gamma X_{it} + \epsilon_{it}, \tag{2}$$

where f_{it} is an indicator if worker i becomes employed in month t after not being employed in month $t-1$; X_{it} includes the same worker characteristics as in the separations model, but instead of job characteristics, it includes the length of the nonemployment spell in years; an indicator for whether the spell started before the sample; and an indicator for new entrants to the labor market.[4] I include fixed effects for calendar month to capture seasonal dynamics. Standard errors are clustered by month.

The main coefficient results are shown in Panel (b) of Table 1. Starting in first row, Black workers are 0.76 percentage points less likely to move from nonemployment to employment in the reference periods. This effect is strongest for Black men, who are 1.3 percentage point less likely to move from nonemployment to employment than white men. In high unemployment months, the average job-finging rate decreases by 0.62 percentage point, with a stronger effect for men at 0.77 percentage point. Black workers face an especially low job-finding probability in high unemployment months. For the full sample, Black workers are an additional 0.23 percentage point less likely to move into employment, which adds about 30% to the average racial gap. The results are much weaker for men, with a negative but statistically insignificant coefficient on the interaction term. For Black women, the effect is especially strong, with the job-finding rate falling by 0.29 percentage point, or about 80% of the average racial gap.

[4] For nonemployment spells that start before the survey period, respondents are asked when they last held a job, up to two years earlier. This indicator captures those individuals whose spell length is longer than two years prior to the start of the survey.

Table 1: Transition rates by race and aggregate unemployment

(a) Separations: E to N	(1) All	(2) Men	(3) Women
Black	0.09	0.08	0.08
	(0.03)	(0.04)	(0.04)
High UR	0.05	0.14	-0.04
	(0.04)	(0.05)	(0.04)
Black × High UR	-0.08	0.01	-0.13
	(0.05)	(0.07)	(0.07)
N	3,701,235	1,900,483	1,800,752
R^2	0.01	0.01	0.01
Black mean	1.60	1.52	1.66
White mean	1.30	1.17	1.44

(b) Job-finding: N to E	(1) All	(2) Men	(3) Women
Black	-0.76	-1.30	-0.36
	(0.06)	(0.09)	(0.07)
High UR	-0.62	-0.77	-0.53
	(0.09)	(0.11)	(0.07)
Black × High UR	-0.23	-0.10	-0.29
	(0.09)	(0.14)	(0.10)
N	2,226,789	837,928	1,388,861
R^2	0.04	0.05	0.04
Black mean	2.65	2.81	2.53
White mean	2.39	3.01	2.01

The table reports differences in separation and job-finding rates by race and macroeconomic conditions. The units are percentage points. Panel (a) reports the estimates for separation rates from equation (1). Panel (b) reports the estimates for job-finding rates from equation (2). All specifications include controls for age, age-squared, and marital status (interacted with gender in column (1)); education; geographic region; metro area size; calendar month fixed effects. Panel (a) includes controls for industry; occupation; and length of employment spell in years. Panel (b) includes controls for length of nonemployment spell in years; indicator for new entrants; and indicator for unobserved full length of nonemployment spell. Standard errors are clustered by month.

3.2. Transition rates by race and firm size

Given the aggregate patterns of transition rates in the SIPP, I next study how these vary with firm size.

For separations, I modify the framework above to allow for size-specific interactions on the main coefficients of interest,

$$s^N_{ijt} = \alpha_j + \alpha^B_j \text{Black}_i + \beta_j \text{HighUR}_t + \beta^B_j \text{Black} \times \text{HighUR} + \Gamma X_{ijt} + \epsilon_{ijt}, \tag{3}$$

where s^N_{ijt} is the probability that worker i moves from employment at type j firm in month $t-1$ to nonemployment in month t; worker and job characteristics, X_{ijt} are the same as above.

The results are reported in Panel (a) of Table 2. Column (1) repeats the result from Table 1 for comparison. Columns (2)-(5) report the size-specific coefficents of interest from equation (3). The higher separation rate for Black workers is coming from large and small firms, with Black workers facing a 0.18 percentage point higher separation rate at large firms relative to white workers at large firms, and 0.27 percentage point gap at small firms. In high unemployment months, the separation rate generally increases, with the largest increase coming from small firms. The gap in separation rates between Black and white workers does not appear to worsen in high unemployment months, with negative and statistically insignificant coefficients for both large and small firms. Separations from self employment appear to worsen for Black workers.

Turning next to job-finding rates, I modify the linear model to include separate outcome variables for moving into employment at each type of firm,

$$f_{ijt} = \alpha_j + \alpha^B_j \text{Black}_i + \beta_j \text{HighUR}_t + \beta^B_j \text{Black} \times \text{HighUR} + \Gamma_j X_{it} + \epsilon_{it}, \tag{4}$$

where f_{ijt} is the probability of worker i moving from nonemployment in month $t-1$ into employment at a type j firm in month t. The sum of these firm-type specific job-finding rates is equal to the total job-finding rate, $f_{it} = \sum_j f_{ijt}$.

The results are reported in Panel (b) of Table (2). Column (1) repeats the coefficients from the aggregate model, given by equation (2), for comparison. Black workers face lower job finding rates relative to white workers with similar characteristics across all types of employers except government. The gap in job-finding rates at small firms is especially wide, with Black workers facing a 0.59 percentage point lower probability of moving into employment at a small firm. In high unemployment months, the job-finding rate decreases across all types of employers. The gap in job-finding rates between Black and white workers worsens in high unemployment months, with the effect entirely driven by the change in job-finding at large firms. Black workers are 0.23 percentage point less likely to move into any type of employment and 0.24 percentage point less likely to move into large firm employment in high unemployment months.

3.3. Alternative specification

The results that job-finding rates are especially low for Black workers in high-unemployment months and that this is driven by large firms are robust to using a logit model rather than the linear model.

In particular, I use the following model for separations,

$$s_{it}^N = \frac{\exp(\alpha^B \text{Black}_i + \beta \text{High UR}_t + \beta^B \text{Black} \times \text{High UR} + \Gamma X_{it})}{1 + \exp(\alpha^B \text{Black}_i + \beta \text{High UR}_t + \beta^B \text{Black}_i \times \text{High UR}_t + \Gamma X_{it})} \tag{5}$$

in which s_{it}^N is the probability of worker i moving to nonemployment in month t, conditional on being employed in month $t-1$, and controls are the same as the linear version. Standard errors are clustered by month. The estimates for the main coefficients of interest are reported in Panel (a) of Table 3. The first column pools all workers and the second two re-estimate the model separately by gender. Black workers have consistently higher separations to nonemployment than white workers, as seen by the positive coefficient on the Black dummy variable, with a particularly higher rate of separations for Black men. The coefficients can be interpreted as the log difference in the ratios of the separation probability to the job-staying probability for each indicator, for Black relative to white workers. The ratio of separating to job-staying is about 6.5 percent higher for Black workers. This ratio increases by about 4.9 percent when the unemployment rate is high, with the increase concentrated among men. However, we observe negative and statistically insignificant interactions effects for Black workers in high unemployment periods.

Next, I use the following model for job finding,

$$f_{it} = \frac{\exp(\alpha^B \text{Black}_i + \beta \text{High UR}_t + \beta^B \text{Black}_i \times \text{High UR}_t + \Gamma X_{it})}{1 + \exp(\alpha^B \text{Black}_i + \beta \text{High UR}_t + \beta^B \text{Black}_i \times \text{High UR}_t + \Gamma X_{it})} \tag{6}$$

in which f_{it} is the probability of worker i moving to employment in month t, conditional on being nonemployed in month $t-1$, and controls are again the same as in the linear model, with standard errors clustered by month. The estimates for the main coefficients of interest are reported in Panel (b) of Table 3. Conditional on observable characteristics, the Black job-finding rate is significantly lower in general, especially for Black men. Considering the first column, the ratio of job finders to those staying nonemployed is 28% lower for the Black population. In the high unemployment state, the ratio of job-finders to those staying in nonemployment is about 28% lower as well. For the Black population, that ratio is an additional 8% lower, indicating that the changes in job-finding are particularly important for the changes in Black employment in high-unemployment months.

I modify the model of separations to nonemployment to allow for separate effects by employer type,

$$s^N_{ijt} = \frac{\exp(\alpha_j + \alpha_j^B \text{Black}_i + \beta_j \text{High UR}_t + \beta_j^B \text{Black}_i \times \text{High UR}_t + \Gamma X_{it})}{1 + \exp(\alpha_j + \alpha_j^B \text{Black}_i + \beta_j \text{High UR}_t + \beta_j^B \text{Black}_i \times \text{High UR}_t + \Gamma X_{it})} \tag{7}$$

in which s^N_{ijt} is the probability of worker i moving to nonemployment in month t, conditional on being employed at a type j employer in month $t-1$. I estimate coefficients on the race variable and macroeconomic conditions separately by employer type. The worker and firm characteristics are the same as above. To avoid overfitting the model, I do not estimate these separately by firm size. Standard errors are clustered by month.

The results are shown in Panel (a) of Table 4. The first column repeats the results from estimating equation (5), as shown in Table 3. The next four columns report the coefficients interacted with firm size or employer type, from equation (7). Black workers face higher separation rates across employers, with the exception of government employers, and the results are all statistically significant. For the difference in separation rates by high-unemployment months, the results are similarly noisy. Separation rates tend to be higher on average in high unemployment months but lower for Black workers, similar to the aggregate pattern.

Moving next to job-finding rates, I modify the logit model to incorporate multiple outcome variables,

$$f_{ijt} = \frac{\exp(\alpha_j^B \text{Black}_i + \beta_j \text{High UR}_t + \beta_j^B \text{Black}_i \times \text{High UR}_t + \Gamma_j X_{it})}{1 + \exp(\alpha_j^B \text{Black}_i + \beta_j \text{High UR}_t + \beta_j^B \text{Black}_i \times \text{High UR}_t + \Gamma_j X_{it})}, \tag{8}$$

where f_{ijt} is the probability of moving from nonemployment in month $t-1$ to employment at a type j firm in month t, and the sum of these probabilities across types of employers sums to the total, $\sum_j f_{ijt} = f_{it}$. The individual controls are the same as in the aggregate specification. Standard errors are clustered by month.

Panel (b) of Table 4 reports the results. Column (1), again, repeats the results from equation (6). Columns (2)-(5) report the coefficient results from equation (7). To interpret the baseline differences, the relative probability of moving to a large firm rather than staying nonemployed is about 8.5 percent lower for Black workers than for white workers. The same relative probability for small firms is about 63 percent lower for Black workers. Thus the baseline differences in job-finding rates at each type of firm are quantitatively large, consistent with the strong sorting patterns shown earlier.

Next, looking at the differences by high-unemployment months, the probability of moving to a large firm relative to staying nonemployed decreases by about 27 percent for white workers in high unemployment months. The decrease in this ratio for small firms is relatively similar at 28 percent. Meanwhile, for Black workers, the decrease in the relative probability of moving to a large firm falls by an additional 12 percent. Given that the proportional changes are similar for white workers between small and large firms, this change cannot be simply explained by the higher exposure of Black workers to larger firms.

3.4. Heterogeneity by separation type

I explore the separation findings in more detail using individuals' self-reported reasons for jobs ending. For this exercise, I consider all workers employed by large or small firms based on their job start and end dates. I define a separation as the month of the job end date. I then classify each separation as voluntary or involuntary based on the reasons workers report. I compare how these separations change with firm size, race, and aggregate conditions with the following regression,

$$s^k_{ijt} = \alpha_j + \alpha^B_j \text{Black}_i + \beta_j \text{HighUR}_t + \beta^B_j \text{Black} \times \text{HighUR} + \Gamma X_{ijt} + \epsilon_{ijt}, \tag{9}$$

$k \in \{all, vol, invol\}$, and s^k_{ijt} is the total (all), voluntary (vol) or involuntary ($invol$) separation probability for worker i from firm size j in month t; X_{ijt} contains standard worker worker characteristics–age, age-squared, and marital status by gender, education, geographic region, metro area size–as well as job-specific characteristics–job tenure in years, log wage, hours, union membership, and industry.

The main coefficients are reported in Table 5. Starting with total separations reported in Column (1), there is little difference in separation rates for Black workers relative to white workers at either small or large firms. However, Columns (2)-(3) show that there are meaningful differences in separations by type. Black workers are 0.71 percentage point less likely to voluntarily separate from small firms, whereas they are 0.56 percentage point more likely to separate involuntarily. These patterns are smaller in magnitude at large firms with voluntary separations -0.48 percentage point lower and involuntary separations 0.38 percentage point higher.

Similarly, total separations decrease in high unemployment months, by roughly the same amount at large and small firms. This effect is driven by voluntary separations, which decrease by more at small firms, whereas involuntary separations increase at both types of firms, but especially at small firms, with an increase of 0.92 percentage point. There does not appear to be a meaningful extra difference in separations for Black workers at either type of firm in high unemployment months, even when comparing voluntary and involuntary.

3.5. Empirical Summary

Overall, the evidence in this section shows two main patterns. First, Black workers face higher separation rates and lower job-finding rates across firms, but particularly at small firms. Second, in a slack labor market, Black workers face especially lower job-finding rates, particularly at large firms. Appendix B reports additional results. Appendix Tables 16 and 17 report the results from Table 2 separately by gender. Appendix Tables 18 and 19 report the results from Table 5 separately by gender. Appendix Table 20 repeats the main results with a continuous interaction term with the unemployment gap rather than an indicator for top tercile months. Appendix Table 21 presents results with the state-level unemployment rate. The results are robust across measures of aggregate conditions and generally stronger for women than men.

The remainder of the paper will focus on one explanation for why we observe more Black workers employed at large firms and evaluate whether this mechanism generates the two patterns described. I choose to focus on the role of information frictions in the hiring process because it is an explanation that has empirical support in the literature and emphasizing hiring is intuitive, given the importance of the job-finding margin in the empirical results presented. Miller & Schmutte (2021) show that referral networks are important for new hires at small firms, and that given racial differences in entrepreneurship, Black workers have less developed networks at these firms. As firms grow, these referrals become less important and the racial gap in hiring narrows. I will model this mechanism in a concise way as a difference in the precision of the signal about a worker's productivity that varies by race and firm size. This mechanism is also consistent with large firms having more sophisticated human resources departments or experienced hiring managers that allow them to evaluate workers more equitably.

In the model, the only difference between Black and white workers will be this difference in information quality in the hiring process. Thus, the model is not designed to capture the full scope of racial differences in hiring and separations because it fails to explicitly model the many other factors that create disparities in the labor market between Black and white workers, such as employer prejudice (Charles & Guryan, 2008), intergenerational wealth (Toney & Robertson, 2021), interactions with the criminal justice system (Holzer *et al.*, 2005), to name just a few. Nonetheless, it is informative to see that the model directionally produces the empirical finding that job-finding rates for Black workers at large firms are especially sensitive to aggregate conditions in the labor market.

The model will be disciplined by average moments from the data, such as the job-finding rate by firm size and the Black share of employment by firm size. In order to make these moments consistent with the setting of the model, I make two adjustments to the raw data. First, I take the means for white workers in low-unemployment periods as given and then back out the means for Black workers using the gap after conditioning on worker and job characteristics, as described earlier in this section. Given that I do not have differences in industry and education in the model, I want to consider the difference in rates between Black and white workers that cannot be explained by these factors. Second, I restrict my sample to individuals who are nonemployed or employed by a large or small firm in the current period and who were in one of these three categories in the previous period, i.e. I exclude workers who moved into nonemployment from a government employer. I rescale the reference-group mean job-finding rates by a factor of $1/(0.79)$ to account for the fact that large and small firms make up 79% of job-finding for white workers, as reported in the means in Table 2. The conditional gaps and reference-group means are reported in Table 6. I use these estimates and the Black share of the population in the SIPP to construct a set of average moments that will be used in disciplining the model and evaluating its fit. The moments are reported in Table 7.

Table 2: Transition rates by race, aggregate unemployment, and firm type

(a) Separations: E to N	(1) All	(2) Large	(3) Small	(4) Government	(5) Self
Black	0.09	0.18	0.27	-0.30	0.01
	(0.03)	(0.05)	(0.07)	(0.04)	(0.07)
High UR	0.05	0.07	0.10	0.07	-0.01
	(0.04)	(0.05)	(0.06)	(0.08)	(0.04)
Black × High UR	-0.08	-0.11	-0.21	0.05	0.29
	(0.05)	(0.08)	(0.14)	(0.09)	(0.15)
N	3,701,235	3,701,235			
R^2	0.01	0.01			
Black mean	1.60	1.69	2.20	0.82	0.82
White mean	1.30	1.27	1.79	0.96	0.47

(b) Job-finding: N to E	(1) All	(2) Large	(3) Small	(4) Government	(5) Self
Black	-0.76	-0.07	-0.59	0.01	-0.08
	(0.06)	(0.04)	(0.03)	(0.02)	(0.01)
High UR	-0.62	-0.26	-0.22	-0.04	-0.04
	(0.09)	(0.04)	(0.03)	(0.01)	(0.01)
Black × High UR	-0.23	-0.24	0.04	-0.03	0.02
	(0.09)	(0.06)	(0.04)	(0.03)	(0.02)
N	2,226,789	2,226,789	2,226,789	2,226,789	2,226,789
R2	0.04	0.02	0.02	0.01	0.00
Black mean	2.65	1.42	0.74	0.28	0.09
White mean	2.39	1.03	0.87	0.26	0.13

The table reports differences in employer-type specific separation and job-finding rates by race and macroeconomic conditions. The units are percentage points. Panel (a) reports the estimates for aggregate separations rates from equation (1) in column (1) and the interacted coefficients with employer type from equation (3) in columns (2)-(5). Panel (b) reports the estimates for aggregate job-finding rates from equation (2) in column (1) and the estimates for equation (4) with an outcome variable for each employer type in columns (2)-(5). All specifications include controls for age, age-squared, and marital status interacted with gender; education; geographic region; metro area size; calendar month fixed effects. Panel (a) includes controls for industry; occupation; and length of employment spell in years. Panel (b) includes controls for length of nonemployment spell in years; indicator for new entrants; and indicator for unobserved full length of nonemployment spell. Standard errors are clustered by month.

Table 3: Transition rates by race and aggregate unemployment, logit

(a) Separations: E to N	(1) All	(2) Men	(3) Women
Black	0.07	0.09	0.04
	(0.02)	(0.03)	(0.02)
High UR	0.05	0.13	-0.03
	(0.03)	(0.04)	(0.03)
Black × High UR	-0.05	-0.02	-0.06
	(0.03)	(0.05)	(0.05)
N	3,701,235	1,900,483	1,800,752
Pseudo R^2	0.07	0.07	0.06
Black mean	1.60	1.52	1.66
White mean	1.30	1.17	1.44

(b) Job-finding: N to E	(1) All	(2) Men	(3) Women
Black	-0.27	-0.37	-0.19
	(0.02)	(0.03)	(0.03)
High UR	-0.28	-0.29	-0.27
	(0.05)	(0.05)	(0.05)
Black × High UR	-0.08	-0.06	-0.09
	(0.04)	(0.05)	(0.05)
N	2,226,789	837,928	1,388,861
Pseudo R^2	0.21	0.22	0.20
Black mean	2.65	2.81	2.53
White mean	2.39	3.01	2.01

The table reports differences in separation and job-finding rates by race and macroeconomic conditions from a logit model. Panel (a) reports the estimates for separation rates from equation (5). Panel (b) reports the estimates for job-finding rates from equation (6). All specifications include controls for age, age-squared, and marital status (interacted with gender in column (1)); education; geographic region; metro area size; calendar month fixed effects. Panel (a) includes controls for industry; occupation; and length of employment spell in years. Panel (b) includes controls for length of nonemployment spell in years; indicator for new entrants; and indicator for unobserved full length of nonemployment spell. Standard errors are clustered by month.

Table 4: Transition rates by race, aggregate unemployment, and firm type, logit

(a) Separations: E to N	(1) All	(2) Large	(3) Small	(4) Government	(5) Self
Black	0.07	0.12	0.12	-0.31	0.23
	(0.02)	(0.03)	(0.03)	(0.05)	(0.09)
High UR	0.05	0.06	0.07	0.08	-0.06
	(0.03)	(0.04)	(0.04)	(0.09)	(0.06)
Black × High UR	-0.05	-0.07	-0.11	0.10	0.37
	(0.03)	(0.05)	(0.07)	(0.10)	(0.17)
N	3,701,235	3,701,235			
Pseudo R^2	0.07	0.07			
Black mean	1.60	1.69	2.20	0.82	0.82
White mean	1.30	1.27	1.79	0.96	0.47

(b) Job-finding: N to E	(1) All	(2) Large	(3) Small	(4) Government	(5) Self
Black	-0.27	-0.10	-0.62	0.06	-0.62
	(0.02)	(0.03)	(0.03)	(0.06)	(0.10)
High UR	-0.28	-0.27	-0.28	-0.13	-0.34
	(0.05)	(0.05)	(0.05)	(0.06)	(0.07)
Black × High UR	-0.08	-0.12	0.01	-0.17	0.13
	(0.04)	(0.05)	(0.05)	(0.11)	(0.17)
N	2,226,789	2,226,789			
Pseudo R^2	0.21	0.17			
Black mean	2.65	1.42	0.74	0.28	0.09
White mean	2.39	1.03	0.87	0.26	0.13

The table reports differences in employer-type specific separation and job-finding rates by race and macroeconomic conditions using a logit model. Panel (a) reports the estimates for aggregate separations rates from equation (5) in column (1) and the interacted coefficients with employer type from equation (7) in columns (2)-(5). Panel (b) reports the estimates for aggregate job-finding rates from equation (6) in column (1) and the estimates for the multinomial logit given by equation (8) with an outcome variable for each employer type in columns (2)-(5) and remaining nonemployed as the reference outcome. All specifications include controls for age, age-squared, and marital status (interacted with gender in column (1)); education; geographic region; metro area size; calendar month fixed effects. Panel (a) includes controls for industry; occupation; and length of employment spell in years. Panel (b) includes controls for length of nonemployment spell in years; indicator for new entrants; and indicator for unobserved full length of nonemployment spell. Standard errors are clustered by month.

Table 5: Separation rate heterogeneity

	(1) All	(2) Voluntary	(3) Involuntary
Large	-0.08	-0.07	-0.04
	(0.05)	(0.08)	(0.06)
Small × Black	-0.05	-0.71	0.56
	(0.12)	(0.18)	(0.16)
Large × Black	-0.01	-0.48	0.37
	(0.07)	(0.12)	(0.09)
Small × HighUR	-0.26	-0.99	0.92
	(0.07)	(0.10)	(0.09)
Large × HighUR	-0.22	-0.82	0.63
	(0.05)	(0.07)	(0.06)
Small × Black × HighUR	-0.10	-0.08	-0.06
	(0.20)	(0.28)	(0.30)
Large × Black × HighUR	-0.19	-0.26	-0.06
	(0.12)	(0.17)	(0.16)
N	1,566,300	1,556,118	1,556,118
R^2	0.02	0.02	0.01
Black mean	2.38	2.31	1.93
White mean	2.15	2.41	1.48

The table reports differences in size-specific and reason-specific separation rates by race and macroeconomic conditions given by equation (9). The units are percentage points. The sample includes all workers who report a job at a large or small firm. The outcome variable in column (1) is an indicator equal to 1 if the worker reports the job ending that month. The outcome variables in columns (2)-(3) are indicators equal to 1 if the worker reports the job ending and gives an involuntary or voluntary reason for it, respectively. All specifications include controls for age, age-squared, and marital status interacted with gender; education; geographic region; metro area size; calendar month fixed effects; job tenure in years; log wage; hours; union membership; and industry. Standard errors are clustered by month.

Table 6: Empirical results for model

	(1) Large Job-finding	(2) Small Job-finding	(3) Large Separation	(4) Small Separation	(5) Large share of employment	(6) Employment
Conditional gaps:						
Black	-0.21	-0.70	0.18	0.28	10.26	-6.22
	(0.04)	(0.03)	(0.04)	(0.08)	(0.44)	(0.35)
High UR	-0.49	-0.39	0.07	0.11	0.92	-2.77
	(0.02)	(0.02)	(0.02)	(0.04)	(0.27)	(0.17)
Black × High UR	-0.28	0.01	-0.11	-0.20	-0.29	-0.99
	(0.06)	(0.04)	(0.07)	(0.14)	(0.69)	(0.53)
Reference group mean						
White, Low UR	1.37	1.17	1.40	1.53	62.86	57.35
	(0.02)	(0.01)	(0.01)	(0.02)	(0.15)	(0.15)

The table reports conditional gaps from the data to be used in the model analysis. The reference group mean reports the mean outcome variable for white workers in non-high unemployment periods. The mean job-finding rates in columns (1) and (2) are scaled up by a factor of 1/(0.79) to account for the fact that large and small firms make up 79% of job-finding for white workers, as reported in the means in Table 2. Columns (1)-(2) and (3)-(4) replicate the results from Table 2 with the sample excluding non-private firm employees. Standard errors are constructed using a block bootstrap by person, within each SIPP panel.

Table 7: Data moments for model

Large firm share of employment	64.10	(0.15)
Job-finding rate	2.40	(0.02)
Large	1.34	(0.02)
Small	1.06	(0.01)
Separation rate	1.47	(0.01)
Large	1.43	(0.01)
Small	1.56	(0.02)
Black share of population	13.26	(0.10)
Nonemployment	14.90	(0.15)
Large firm employment	13.68	(0.16)
Small firm employment	8.97	(0.15)

The table reports moments from the data to be used in the model analysis. The Black share of the population is used to construct all other moments from the reference group means and gaps reported in Table 6. Standard errors are constructed using a block bootstrap by person, within each SIPP panel.

4. Model

The empirical results demonstrate that Black workers face persistently lower job-finding rates at small firms, in excess of what would be predicted by worker characteristics. When the economy contracts, the job-finding rates for Black workers at large firms decrease proportionately more than the job-finding rates at small firms. In this section, I develop a quantitative model that embeds information frictions 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.

4.1. Environment

4.1.1. 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 nonemployed workers at the start of period t (with $1 - u_t$ the mass of employed workers). Nonemployed workers receive flow utility b. Firms are owned by workers with dividends distributed in lump sum.

There are two types of workers, $g \in \{W, B\}$, with (a fixed) fraction $\pi < \frac{1}{2}$ in B (minority group). Let π_t^u be the share of B workers in the nonemployed population (u_t) at time t, which is determined endogenously by separations and hiring decisions by firms. Group membership will only affect the access workers have to matching technology, to be described in the next section.

4.1.2. Firms

There are two types of firms indexed by their (fixed) idiosyncratic productivity z. They share a common aggregate productivity a_t, which will be subject to shocks. They use labor to produce a single good with decreasing returns to scale production technology,

$$y_t = a_t z n_t^{\alpha}$$

4.1.3. Matching and hiring process

This is a random search model with information frictions in the hiring process (Baydur, 2017, Jarosch & Pilossoph, 2019). Firms post vacancies (v) to attract matches. This 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 nonemployed workers depends on market tightness, θ_t, where the probability that a vacancy attracts a worker is $q(\theta)$, the probability a nonemployed worker meets a firm is $\theta q(\theta)$, and $\theta = \frac{V}{U}$ is market tightness. Given that this is random search, workers do not target particular types of firms and firms cannot target their vacancies to particular workers. A worker matches to a type z firm proportional to their share of vacancies, while a firm matches to a type g worker proportional to their share in the nonemployed pool.

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, ($\tilde{F}(\tilde{x})$), which determines the likelihood the worker will be productive. The match quality is unobservable to the worker and the firm, but both observe a signal of the match quality, (s). The signal follows the inspection technology form of Menzio & Shi (2011), where the firm observes the true match quality with probability $p(g, z)$, which depends on worker group g and firm type z. With probability $1 - p(g, z)$, the firm observes another iid draw from the same distribution. Thus, the firm forms a posterior belief (x) about the worker's productivity conditional on their signal, according to

$$x = p(g, z)s + (1 - p(g, z))\mathbb{E}[s] \tag{10}$$

This friction is meant to capture differences in referral networks that affect the information firms have about potential hires, as in Miller & Schmutte (2021). It is similar to the statistical discrimination literature (e.g. Black (1995), Lang & Lehmann (2012)). These papers aim to explain racial wage gaps through differences in signal quality.

Using these beliefs, the firm must decide which matches to hire. The firm chooses a group-specific threshold rule, $x^*(g, z)$ such that it hires all matches from that group with an 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.

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.

4.2. Optimization

4.2.1. Firms' Problem

The firm chooses vacancies v and hiring standards x_B, x_W, which implicitly define the number of hires $\{h_g\}$, the expected productivity of the hires $\{\hat{x}(x_g, p(g, z))\}$, and next period employment $\{n'_g\}$ for each group

$$J_t(n_B, n_W, z) = \max_{v \geq 0, x_g} -c_v(z)v + a_t z(n')^\alpha \tag{11}$$

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

s.t.

$$n' = \sum_g n'_g \tag{12}$$

$$n'_g = (1-\delta_t)n_g + \hat{x}(x_g, p(g, z))h_g \tag{13}$$

$$h_g = \frac{u_{gt}}{u_t} q(\theta_t) v (1 - F(x_g | p(g, z))) \tag{14}$$

$$\bar{x}(p(g, z)) - p(g, z) \leq x_g \leq \bar{x}(p(g, z)) \tag{15}$$

where $\bar{x}(p)$, $F(x|p)$, and $\hat{x}(x,p)$ capture features of the distribution of posterior beliefs a firm forms about match productivity, given the quality of the signal p and the exogenous distribution of match productivity, $F(\cdot)$.

$$\bar{x}(p) = p + (1-p)\mathbb{E}[x] \tag{16}$$

$\bar{x}(p)$ is the maximum posterior belief about match productivity the firm receives, given its signal quality p. For example, if the firm receives no information about match productivity ($p = 0$), the posterior belief about the worker with the highest observed signal is the unconditional expectation, whereas if it receives full information about match productivity ($p = 1$), the worker with the highest signal will be productive with probability 1.

$$F(x|p) = F\left(\frac{x - (1-p)\mathbb{E}[x]}{p}\right) \tag{17}$$

$F(x|p)$ is the cumulative distribution of posteriors conditional on signal quality p, and $\hat{x}(x,p)$ is the expected productivity of a hire conditional

$$\hat{x}(x,p) = \frac{\int_x^{\bar{x}(p)} y dF(y|p)}{1 - F(x|p)} \tag{18}$$

where $F(\cdot)$ is the exogenous distribution of match quality.

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

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

$$q(\theta_t)v = \frac{h_B}{\frac{u_{Bt}}{u_t}(1 - F(x_B|p(B,z)))} = \frac{h_W}{\frac{u_{Wt}}{u_t}(1 - F(x_W|p(W,z)))} \tag{19}$$

4.2.2. Worker's Problem

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

$$V_t^n(g,z) = w_t^n(n', z, g) + \beta \mathbb{E}_t \left[V_{t+1}^u(g) + (1-\delta)(V_{t+1}^n(g,z) - V_{t+1}^u(g)) \right] \tag{20}$$

Newly hired workers can be paid different wages and face higher separation rates, captured in the value function $V_t^h(g,z)$[5]

$$V_t^h(g,z) = w_t^h(x_g(z), n', z, g) + \beta \mathbb{E}_t \left[V_{t+1}^u(g) + \hat{x}(x_g(z), p(g,z))(1-\delta)(V_{t+1}^n(g,z) - V_{t+1}^u(g)) \right] \tag{21}$$

where $\hat{x}(x_g(z), p(g,z))$ is the probability that the worker is productive conditional on the firm's hiring threshold $x_g(z)$ and signal quality $p(g,z)$. For nonemployed workers, the value function is

$$\begin{aligned} V_t^u(g) &= b + \beta \mathbb{E}_t V_{t+1}^u(g) \\ &+ \underbrace{\beta \mathbb{E}_t \left[\theta_{t+1} q(\theta_{t+1}) \sum_z \frac{\mu(z) v^(z)}{V} (1 - F(x_g(z)|p(g,z)))(V_{t+1}^h(g,z) - V_{t+1}^u(g)) \right]}_{\Omega_t(g)} \end{aligned} \tag{22}$$

where $v(z)$ is the equilibrium number of vacancies posted by a firm of type z, $\mu(z)$ is the mass of type z firms per worker in the economy, V is the aggregate number of vacancies, and $x_g(z)$ is the firm's equilibrium threshold rule.

[5] For simplicity, I am going to ignore differences in individual productivity probabilities across new hires within the same group and firm. From the firm's perspective, the problem would be unchanged if I allow wages and value functions to depend on an individual's specific x.

4.2.3. 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. This is a standard bargaining rule in models with endogenous firm size, such as Baydur (2017) and Elsby & Michaels (2013). Let $D_t(\{\tilde{n}_g\}, \{h_g\}, \{x_g\}, z)$ be the firm value after vacancy posting is sunk and hiring thresholds have been set,

$$\begin{aligned} D_t(\{\tilde{n}_g\}, \{h_g\}, \{x_g\}, z) = & a_t z(n')^\alpha - \sum_g \left(\tilde{n}_g w^n(n', z, g) + h_g w^h(x_g, n', z, g)\right) \\ & + \beta \mathbb{E}_t J_{t+1}(n'_B, n'_W, z) \\ & \text{s.t.} \\ & n'_g = \tilde{n}_g + \hat{x}(x_g, p(g, z))h_g \end{aligned} \tag{23}$$

where $\tilde{n}_g = (1 - \delta)n_g$ is the number of existing employees, h_g is the number of new hires as defined in equation (14), and $\hat{x}(x_g(z), p(g, z))$ is the expected productivity of new hires as defined in equation (18).

Firms and workers split the surplus according to the following rules

$$\phi D_{t,\tilde{n}_g} = (1 - \phi)\left(V_t^n(g, z) - V_t^u(g)\right) \tag{24}$$

$$\phi D_{t,h_g} = (1 - \phi)\left(V_t^h(g, z) - V_t^u(g)\right) \tag{25}$$

where the left-hand-side is the marginal surplus to the firm of having one more employee from that group multiplied by the worker bargaining power, and the right-hand-side is the marginal surplus to the worker of being employed by a type z firm rather than nonemployed, multiplied by the firm bargaining power.

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

$$w^n(n', z, g) = \frac{\alpha\phi}{1-\phi+\alpha\phi} a_t z n'^{\alpha-1} + (1-\phi)(b + \Omega_t(g)) \tag{26}$$

$$w^h(x_g, n', z, g) = \hat{x}(x_g, p(g,z)) \frac{\alpha\phi}{1-\phi+\alpha\phi} a_t z n'^{\alpha-1} + (1-\phi)(b + \Omega_t(g)) \tag{27}$$

where $\Omega_t(g)$ is the value of searching next period for a worker from group g as defined in equation (22). This term is included in addition to the flow value of nonemployment, b, because workers who separate are not able to search in the following period. Notice that if firms have full bargaining power, $\phi = 0$, then all workers will be paid their outside option, b, and the value of search will disappear, $\Omega_t(g) = 0$.

The full details are provided in Appendix C.

4.2.4. Aggregation

Let $\mu(z)$ be the mass of type z firms (relative to a unit mass of workers). The aggregate nonemployment rate for the minority group evolves according to

$$u_{gt+1} = 1 - \frac{1}{\pi(g)} \sum_z \mu(z) \left(n'_g(z) + h_g(z)(1 - \hat{x}(x_g(z), p(g,z))) \right) \tag{28}$$

where $\pi(g)$ is the share of group g in the population, $\mu(z)$ is the mass of firms of type z, 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 nonemployment rate.

The distribution of employment across firms is given by

$$\Gamma(z) = \frac{\mu(z) \sum_g ((1-\delta)n_g(z) + h_g(z))}{\sum_{\tilde{z}} \mu(\tilde{z}) \sum_g ((1-\delta)n_g(\tilde{z}) + h_g(\tilde{z}))} \tag{29}$$

4.3. Equilibrium

4.3.1. Equilibrium definition

Given exogenous masses of firms $\mu(z)$, a recursive competitive equilibrium for this economy is a list of functions: (i) value functions for firms, $J(n_B, n_W, z)$, (ii) decision rules for vacancies and hiring standards, $v(z), x_g(z)$, (iii) value functions for workers $V^n(g, z)$, $V^h(g, z)$, $V^u(g)$, (iv) wage functions $w^n(n', g, z)$, $w^h(x_g, n', g, z)$, and (v) worker outside option functions $\Omega(g)$, and market tightness θ, a stationary distribution of employment across firms, $\Gamma(z)$, and a stationary distribution of minority workers in unemployment and each employer type, π^u, π^z.

1. *Firm optimization*: Given θ, $\lambda(u)$, $\Omega(g)$, $w^n(n', z, g)$, $w^h(x_g, n', z, g)$, the set of decision rules $v(z), x_g(z)$ solve the firm problem

2. *Worker optimization*: Given $\theta, \Gamma(z)$, $w^n(n', z, g)$, $w^h(x_g, n', z, g)$, and $v(z), x_g(z)$, worker value functions $V^n(g, z)$, $V^h(g, z)$, and $V^u(g)$ solve the worker problem and $\Omega(g)$ is consistent with value functions

3. *Wage bargaining*: $w^n(n', z, g)$, $w^h(x_g, n', z, g)$ 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 minority workers across unemployment and employer types, π^u, π^z is consistent with firm optimization

4.3.2. Firm problem solution

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

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

where

$$
\begin{aligned}
C_t(\Delta_B, \Delta_W) = \min_{\{x_g\}} \sum_g & \frac{\Delta_g}{\hat{x}(x_g, p(g,z))} \left(\frac{c_v(z)}{q(\theta_t)(1-F(x_g|p(g,z)))} + (1-\phi)(b+\Omega_t(g)) \right) \\
& \text{s.t. } (19)
\end{aligned} \tag{30}
$$

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

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

$$
\begin{aligned}
\frac{\partial C_t(\Delta_B, \Delta_W)}{\partial \Delta_g} & + \beta(1-\delta)\mathbb{E}_t\left[(1-\phi)(b+\Omega_{t+1}(g))\right] \\
& = \frac{\alpha(1-\phi)}{1-\phi+\alpha\phi} a_t z (n')^{\alpha-1} + \beta(1-\delta)\mathbb{E}_t\left[\frac{\partial C_{t+1}(\Delta'_B, \Delta'_W)}{\partial \Delta'_g}\right]
\end{aligned} \tag{31}
$$

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

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

$$\frac{\partial C_t(\Delta_B, \Delta_W)}{\partial \Delta_g} = \frac{(1-\phi)(b+\Omega_t(g))}{x_g} \tag{32}$$

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

Equations (31) and (32) can be combined to show the relationship between the hiring thresholds for the two groups.

$$\begin{aligned} 0 =& \frac{(b+\Omega_t(B))}{x_B} - \beta(1-\delta)\mathbb{E}_t\left[(b+\Omega_{t+1}(B))\frac{1-x'_B}{x'_B}\right] \\ &- \frac{(b+\Omega_t(W))}{x_W} + \beta(1-\delta)\mathbb{E}_t\left[(b+\Omega_{t+1}(W))\frac{1-x'_W}{x'_W}\right] \end{aligned} \tag{33}$$

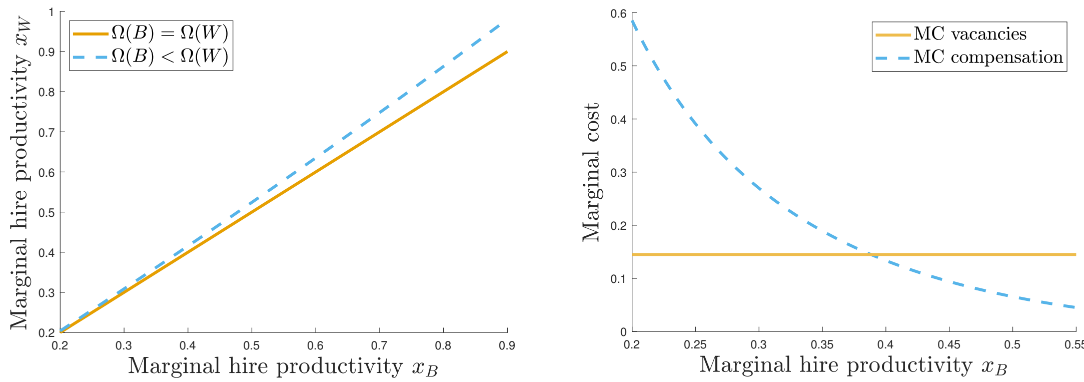
Panel (a) of Figure 4 shows this relationship in steady state where $\Omega_t(g) = \mathbb{E}[\Omega_{t+1}(g)] = \Omega(g)$, using the calibration discussed in the next section. First, the orange (solid) line shows that if the outside options of both groups are equal, then the firm will choose the same marginal hire productivity across groups. If the outside option of the minority group is lower $\Omega(B) < \Omega(W)$, as shown by the blue (dashed) line, the firm is willing to choose a lower productivity threshold for the minority group because they can compensate them less. Notice that this relationship between x_B and x_W is determined by market conditions and all firms in the economy face the same tradeoff between marginal hire productivities. However, firms may choose to locate at different points on the frontier, depending on the solution to the cost minimization problem.

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

$$\frac{c_v(z)}{q(\theta_t)} = \sum_g \frac{u_{gt}}{u_t}(1-\phi)(b+\Omega_t(g))\frac{(\hat{x}(x_g, p(g,z)) - x_g)}{x_g}(1-F(x_g|p(g,z))) \tag{34}$$

The left side of equation (34) is the marginal vacancy cost, which is constant due to the

Figure 4: Marginal hire productivity between groups



(a) (b)

linear vacancy technology. The right side of equation (34) is the marginal benefit of posting an additional vacancy, which can be thought of as the marginal cost of compensation. If the firm posts an extra vacancy, it can maintain the same level of hiring by being more selective about the workers it hires, thus reducing the compensation paid to unproductive workers. In the limit, if firms hired only the workers with the highest expected productivity, this cost would go to zero. As they lower the threshold, they accept more workers who will separate. Thus the compensation cost is decreasing with firm selectivity. The firm's optimal decision is at the intersection of these two curves, shown in Panel (b) of Figure 4.

5. Calibration

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

I need two functional form assumptions before describing the parameters. I use a Cobb-Douglas matching function as in Petrongolo & Pissarides (2001)

$$q(\theta) = \zeta\theta^{-\psi}$$

I also need an exogenous distribution of match quality. I will 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.

5.1. Fixed parameters

Given the monthly frequency, I set the discount factor β to 0.996 to match a quarterly interest rate of 0.012. I set the production curvature α to 0.677 as in Baydur (2017). I use a standard Cobb-Douglas matching technology with matching elasticity ψ 0.6 as in Petrongolo & Pissarides (2001).

I set the share of large firms to 0.02 to match the share of firms with 100 or more employees, excluding firms with zero employment, from 1997 Census data, as reported by Axtell (2001). This is the same threshold for defining large firms that I use in the SIPP, and the time period is consistent with my sample that starts in 1996. The aggregate productivity a scales the absolute value of firm size up, and I choose a value of 4.2, which corresponds to small firms having about 30 employees in equilibrium and large firms having 2700. The minority share of the population is fixed at 0.13 based on the share of Black relative to white population in the SIPP, as reported in Table 7.

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. Given a target for market tightness, θ and the fixed parameter value of ψ, this can be expressed as

$$\zeta\theta^{1-\psi} \sum_{z} \sum_{g} \frac{v(z)}{v} \frac{u_g}{u} (1 - F(x(g, z)))$$

Thus given a target of the job-finding rate from the data, ζ governs how selective the firm is. If ζ is low, then the share of matches that are hired increases, whereas if ζ is high, this share decreases. As a baseline, I select ζ such that the weighted average of the hired share of matches is 8%, which corresponds to the inverse of the average number of applications received per hire in Barron *et al.* (1997). This parameter choice is important because when firms are more selective, this leads to a more negative gap in hiring between minority and majority workers.

Finally, I choose a normalization for the signal quality for majority workers. I use the same normalization across large and small firms because I am allowing vacancy costs to vary by firm size and I cannot separately identify these parameters. What matters is the gap in signal qualities between workers across groups within the same firm.

Table 8: Fixed Parameters

Parameter	Meaning	Value	Source
β	Discount factor	0.996	Quarterly interest rate 0.012
α	Production curvature	0.677	Baydur (2017)
ψ	Matching elasticity	0.6	Petrongolo & Pissarides (2001)
υ	Share of large firms	0.02	Axtell (2001)
a	Aggregate productivity	4.2	Relative sizes
π	Minority share population	0.133	SIPP
ζ	Matching scale	.342	Avg. hired share 0.08
p_W	Majority signal quality	0.99	Normalization

5.2. Fitted parameters

The remaining parameters are chosen in two parts. For the first four, I use moments from other papers to solve for parameters that affect scaling of the model, given the other parameter values. For the next six, I estimate them using generalized method of moments (GMM), allowing the scale parameters to update with each iteration. I construct the weight matrix for GMM using a block-bootstrapped variance-covariance matrix.

For the scale parameters, I target a market tightness of 0.72 as in Elsby & Michaels (2013) by solving for the mass of firms per worker, μ, consistent with this value. Following the strategy of Baydur (2017), I normalize b such that the equilibrium value of nonemployment for the majority group ($b + \Omega(W)$) is equal to 1. I solve for the value of ϕ such that the ratio of b to average productivity (Y/N) is 0.73. The shape of the match quality distribution governs the relative selectivity at small versus large firms. I solve for γ such that large firms hire 5% of their matches, which is the inverse of the number of applications received per hire at firms with 100 or more employees in Barron *et al.* (1997). The equivalent figure at small firms is 10% and left as an untargeted moment.

The remaining six parameters affect all of the moments but I will discuss the identification intuition. Appendix D provides additional details. The exogenous separation rate δ is identified by the average separation rate. The vacancy costs by firm size are identified by the job-finding rates by firm size. To see this, return to the firm's selectivity decision in Panel (b) of Figure 4. An increase in the vacancy cost shifts the marginal cost of vacancies up (blue line), which leads the firm to be less selective, or hire more of its matches, holding fixed the number of hires. This corresponds to a decrease in the number of vacancies the firm needs to post to attract that number of matches. These two effects together map to the job-finding rate at each firm. The relative productivity of large firms, $\frac{z(L)}{z(S)}$ is identified by the employment share at large firms. If the model had no heterogeneity other than differences in firm productivity, large firms would make the same decisions as small firms but with more workers, because $z(L)$ would lead them to hire until their marginal product of labor was the same.

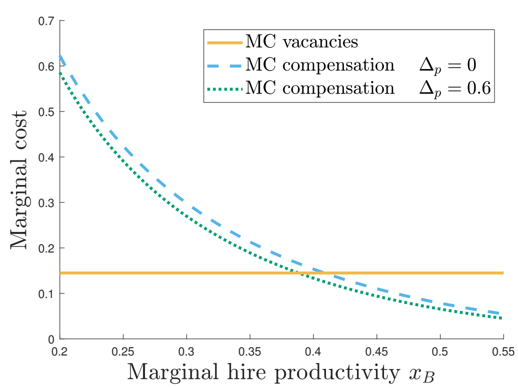
The final estimated parameters are the signal gaps at large and small firms. These are identified by the minority share of employment at each type of firm. Consider the partial equilibrium effects of increasing the signal quality gap between majority and minority workers for the firm's optimal threshold solution in equation (34). Holding fixed the minority share of nonemployment, workers' outside options, and market tightness, an increase in the signal quality gap will make firms slightly more lenient in their hiring, as the information is not as informative. This can be observed by the shift in the marginal cost of compensation curve in Panel (a) of Figure 5 from the blue (dashed) line to the green (dotted) line. Increasing the signal gap from 0 to 0.4 leads to a decrease in the optimal threshold of 0.01. The larger effect is that as the signal gap increases, there is a smaller mass of minority workers with a

Table 9: Fitted Parameters

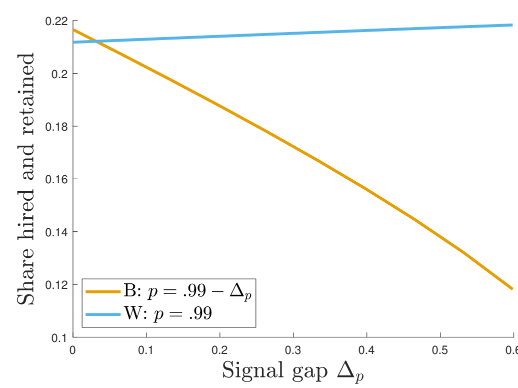
Parameter	Meaning	Baseline
Scale parameters		
μ	Number firms/worker	0.007
b	Flow value unemp	0.998
ϕ	Bargaining power	0.259
γ	Match quality shape	3.28
Estimated parameters		
δ	Exog. separation	0.012
$c_v(L)$	Vacancy cost	0.001
$c_v(S)$	Vacancy cost	0.060
$\frac{z(L)}{z(S)}$	Relative productivity	4.158
$\Delta_p(L)$	Signal gap, large	0.121
$\Delta_p(S)$	Signal gap, small	0.598

signal above the chosen threshold, and the average productivity conditional on being above that threshold also decreases.[6] The result is that the share of minority workers who are hired and retained in the next period drops, as seen in Panel (b) of Figure 5, and representation of minority workers falls.

Figure 5: Signal quality gap and firm's decision



(a)



(b)

Table 10: Moments, percentage points

(a) *Targeted*

Moment	Data/Model
Separation rate	1.47
Employment share	
Large	64.10
Job-finding rate	
Large	1.34
Small	1.06
Minority share	
Large	13.68
Small	8.97
Hired share matches*	
Large	5.02

(b) *Untargeted*

Moment	Data	Model
Separation rate		
Large	1.43	1.28
Small	1.56	1.82
Job-finding gap (B-W)		
Large	-0.21	-0.07
Small	-0.70	-0.26
Separation gap (B-W)		
Large	0.18	0.11
Small	0.28	0.70
Hired share matches*		
Small	10.04	31.63

The units are percentage points. Panel (a) reports the moments that were targeted in the model calibration, which match the data exactly. Panel (b) reports untargeted moments in the model and the data. The data moments are all calculated in the SIPP, except for the hired share of matches, indicated by the *. These are imputed from the inverse number of applications received per hire by firms with over/under 100 employees, as reported by Barron *et al.* (1997).

5.3. Model fit

The model fits the targeted moments almost exactly, with values shown in Panel (a) of Table 10. Panel (b) shows the fit for untargeted moments. I match the average separation rate by construction, but the model matches the distribution across firm size reasonably well. I target the minority share of employment by firm size but not the gaps in job-finding and separations that contribute to them. The model underestimates the job-finding gaps by both types of firms, but still captures that the gap is wider at small firms. Similarly, it captures that the separation gap is higher at small firms. It overestimates the small firm gap while underestimating the large firm gap, similar to the pattern in overall separations. The imperfect fit in terms of hiring and separation gaps is to be expected as the only difference between groups in the model is the hiring process, whereas in reality workers face differences in many other aspects of the employment process. Finally, the small firms in the model are less selective than in the survey estimates from the data, as reported in Barron *et al.* (1997).

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

6. Counterfactuals

6.1. Low vs. high productivity

I use the quantitative model to consider a permanent negative shock to aggregate productivity, a. 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 job finding for white workers matches the empirical average decrease in high unemployment period, as reported in Table 6.

Table 11 reports the results of this exercise for job-finding. By construction, the data and model match exactly in the first row for the total change in job finding for white workers. The next two rows show that the model is relatively consistent with the data in terms of the shares attributed to each type of firm.

Table 11: Steady state comparison

Changes: low - high productivity	**Data**	**Model**
White job finding rate	-0.873	-0.873
Large	-0.487	-0.463
Small	-0.386	-0.410
Job finding gap	-0.275	-0.300
Large	-0.281	-0.248
Small	0.006	-0.052

This table shows the comparison between the low productivity relative to high productivity steady state. The units are percentage points. The low productivity is 0.068 log points below high productivity, chosen such that the difference in the white job finding 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 6, which show the average difference in the size-specific job-finding rates when the unemployment gap is high.

The second group of Table 11 shows the difference in the job-finding gap between steady states. In the data the job-finding gap is 28 basis points worse in the high unemployment periods and the model overshoots that, with the gap worsening by 30 basis points. Looking at the split between large and small firms, the model captures that this difference is strongest for large firms. Using the model, we can decompose why the difference is larger for large

Table 12: Job-finding gap components

	Total gap	Matching rate	Vacancy share	Relative selectivity
Large firm				
High a	-0.066	0.300	0.888	-0.246
Low a	-0.313	0.228	0.894	-1.537
Small firm				
High a	-0.260	0.300	0.132	-7.738
Low a	-0.312	0.228	0.127	-12.884

This table shows the components of the job-finding gap between Black and white workers in the model by firm size and aggregate productivity state. A negative gap means Black workers are finding jobs at lower rates than white workers. The first column, in percentage points, is the product of the next three columns, defined as in equation 35. The first two are expressed as fractions and the last is in percentage points.

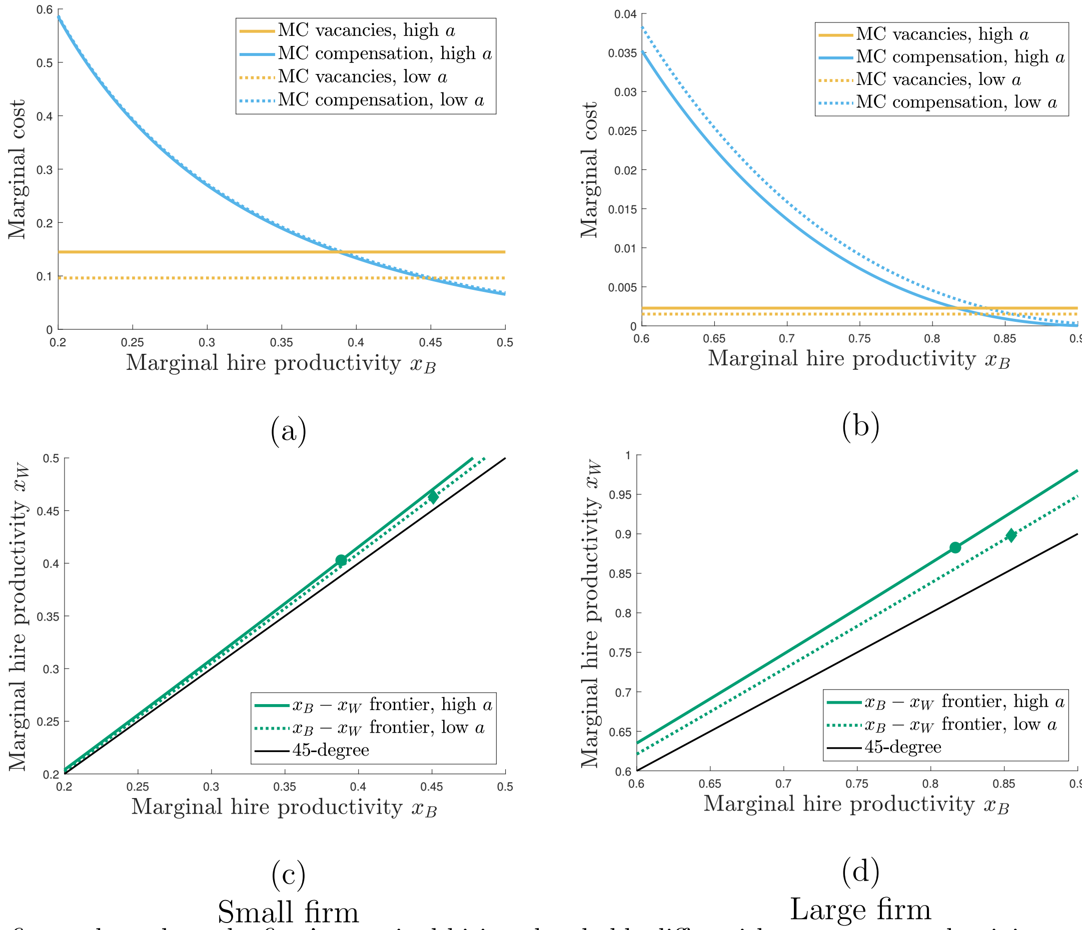
firms. To start, the job finding gap at a firm of type z is

$$\underbrace{\theta q(\theta)}_{\text{matching rate}} \underbrace{\frac{\nu(z)v(z)}{\sum \nu(z)v(z)}}_{\text{vacancy share}} \underbrace{\Big((1-F(x_B|p(B,z))) - (1-F(x_W|p(W,z)))\Big)}_{\text{relative selectivity}} \tag{35}$$

which is a product of three terms. The first is the matching rate component, resulting from the decrease in market tightness, which is the same across all firms. The second is the vacancy share component. The last is the relative selectivity component, or the hiring gap conditional on matching at the type z firm.

These components are itemized in Table 12 for small and large firms in the high and low productivity states. Looking at the first column, we see the key pattern that although the job finding gap is smaller at large firms than small firms in the high productivity steady state, it decreases by more when we move from high productivity to low productivity. This change is primarily driven by the decrease in relative selectivity at both types of firms, shown in the last column. In the high productivity steady state, large firms hired 0.25 ppt fewer Black matches than white, whereas small firms hired 7.7 ppt fewer. In the low productivity state, this gap widens to 1.5 ppt at large firms and 12.9 ppt at small firms. The change in selectivity is thus bigger in proportional terms at large firms, though it is bigger in levels at small firms. The change in selectivity at large firms is amplified by the the disproportionate share of vacancies posted by large firms.

Figure 6: Change in selectivity with aggregate productivity



This figure shows how the firm's marginal hiring thresholds differ with aggregate productivity. Panels (a) and (b) show the tradeoff in the firm's decision between vacancy posting and selectivity. The orange lines are the marginal cost of vacancies, $c_v(z)/q(\theta)$. The blue lines are the marginal cost of compensation, defined as the right-hand side of (34). Both firms are more selective in the low productivity steady state, as the intersection of the dotted lines is to the right of the intersection of the solid lines. Panels (c) and (d) show how this affects selectivity for majority workers using the relationship in equation (31). In the low productivity state, the outside options become more equal and the frontier shifts closer to the 45-degree line, as shown by the dotted line. The dots represent the threshold choices in the high productivity state and the diamonds are the threshold choices in the low productivity state.

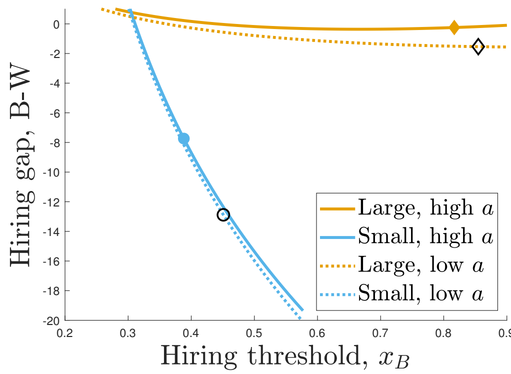
The intuition for the worsening in relative selectivity at both types of firms can be understood by returning to the firm's marginal cost condition in equation (34). When market tightness is lower, firms match with more workers per vacancy, shifting the marginal vacancy cost curve down. This direct effect is illustrated in Panels (a) and (b) of Figure 6 as the difference between the solid and dotted orange lines. It is cheaper for firms to be selective about which workers they hire in the low productivity steady state. This is shown by the intersections of the dotted orange lines at higher marginal productivities of minority workers for both firms.

The selectivity decisions are also influenced by indirect effects, through workers' outside options and the minority share of nonemployment, which affect the marginal cost of compensation. These effects are much smaller for the small firms, as shown by the difference between the solid and dotted blue lines in Panel (a) relative to Panel (b). The shift in the marginal compensation cost curve is the result of two opposing forces. First, in the low productivity steady state, all workers face worse prospects if they join the nonemployed pool, which lowers the endogenous value of nonemployment, $\Omega(g)$, for both groups of workers. Thus, the terms inside the summation in equation (34) are smaller, driving down the marginal cost curve. The second effect is happening through a narrowing of the outside option gap. Because white workers enjoyed more surplus from employment, as this surplus decreases it causes this value to fall more for white workers than Black.[7] Equation (31) shows that the relative selectivity between Black and white workers depends on the gap in outside options. Because Black workers earn lower wages, firms are willing to set a lower marginal productivity threshold for this group. As the outside option gap narrows in the low productivity steady state, this incentive weakens, leading the firm to set marginal thresholds closer to equality between Black and white workers. Panels (c) and (d) show that this effect is stronger at large firms because they are more selective. This shift in relative selectivity causes the overall change in the marginal cost of compensation to be positive, as illustrated in Panels (a) and (b). Intuitively, for a given marginal productivity for Black workers, the firm is now going to hire more white workers with a lower likelihood of being productive, which drives up marginal compensation costs, in spite of average compensation being lower.

To summarize, the worse signal quality for minority workers at both types of firms means that they are hired less in response to a permanent negative productivity shock. At small firms, this is driven by the direct effect of becoming more selective due to the

[7] The narrowing of the outside option gap can be thought of as a narrowing of the racial wage gap. Biddle & Hamermesh (2013) uses data from the CPS to show that the wage gap between Black and white workers is less severe with negative aggregate shocks, which would be consistent with the model prediction. I do not see a significant relationship in either direction between the racial wage gap and the business cycle in the SIPP.

Figure 7: Hiring gap across firms



This figure shows how the hiring gap at each type of firm varies with the productivity threshold for minority workers. First, the orange and blue solid lines show the relationship between the threshold and the hiring gap at large and small firms in the high productivity steady state. The difference between these curves comes from the gap in signal quality for minority workers. The curve for small firms is generally much lower because the gap in signal quality is worse at these firms. The filled diamond and circle show the high productivity steady state threshold choice and hiring gap for each type of firm. The difference in the location of these points on the x-axis comes from differences in the marginal cost of vacancies. Large firms are more selective because they have a lower marginal cost of vacancies. Finally, the dashed orange and blue curves show the relationship between the threshold and hiring gap in the low-productivity steady state. The black diamond and circle show the low-productivity thresholds and hiring gaps. The hiring gap worsens at large firms primarily due to the indirect effects, shown by the shift from solid to dashed line. The hiring gap worsens at small firms primarily due to the direct effect of moving to the right along the solid curve.

reduced marginal cost of vacancies. At large firms, this is driven by the indirect effect of compensation becoming more equal across groups. These nuances are summarized in Figure 7, which shows the relationship between firm selectivity and the racial hiring gap. The small firm hiring gap worsens in the low productivity state primarily due to movement along the solid high productivity curve (direct effect), whereas the large firm hiring gap worsens due to the shift from the solid high productivity curve to the dotted low productivity curve (indirect effect). These changes summarize the hiring gap conditional on matching at a firm. The total observed changed in the job-finding gap is worse at large firms because their low marginal cost of vacancy posting leads them to attract a disproportionate share of matches, thus amplifying the worsening of the hiring gap.

One limitation of this counterfactual and related dynamic exercises is that as firms get more selective, their separation rates fall. Thus, without further richness on the separations margin, I am not be able to replicate both job-finding and separation patterns with representative small and large firms.

7. Conclusion

This paper starts by shedding light on the interactions between firm types and the Black-white employment gap over the business cycle. Consistent with other evidence on sorting between large and small firms, I show that the job-finding and separation gaps are worse for Black workers at small firms on average. However, when the economy contracts and the overall unemployment rate is higher, Black workers are disproportionately hurt by the drop in job-finding rates at large firms.

I showed that a model of information frictions in the hiring process can directionally generate both the sorting of Black workers towards large firms and the disproportionate impact of large-firm hiring changes on Black employment in response to aggregate productivity changes. Although the initial hiring gap is more negative at small firms, both firms worsen the hiring gap for Black workers when a decrease in productivity leads the economy to contract. The impact of the contraction at large firms is stronger overall because they make up a larger share of matches.

The general setup of this model could be used for any setting in which workers differ in their ability to communicate their productivity to potential employers. One such example could be differences in education. It could also easily include more than two groups. I showed in the background information that Hispanic workers are more likely to work at small firms. There is nothing specific to this model that says that small firms need to have the worse signal quality and indeed it would be interesting to see how the implications vary if another group of workers does not face this size-skewed disadvantage.

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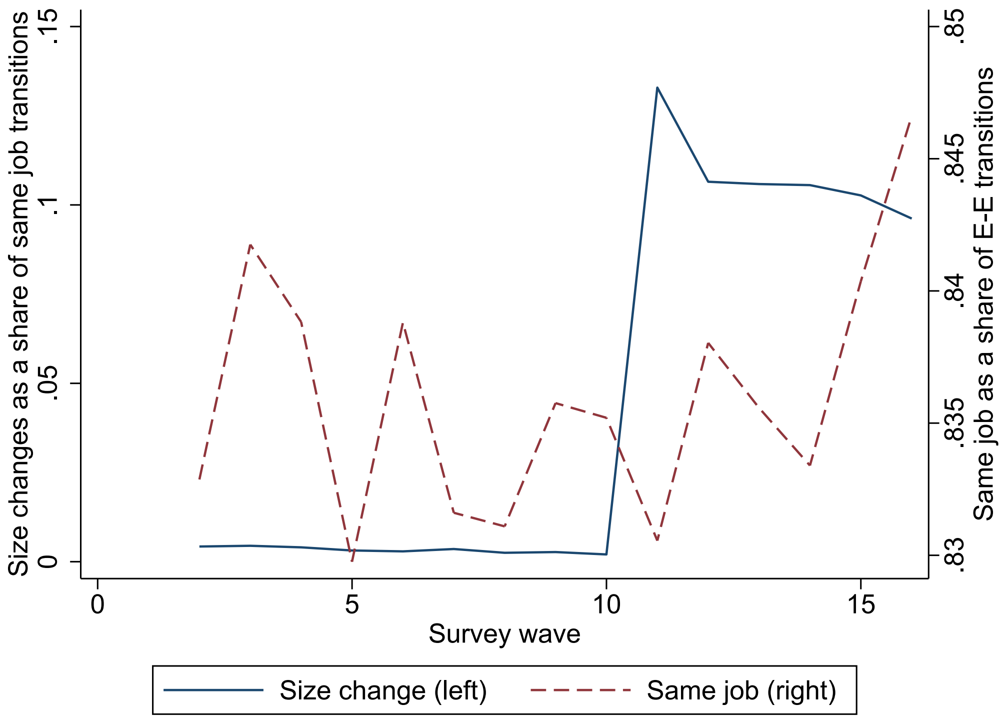
A. Additional information on background empirical facts

A.1. Firm size measurement in the SIPP

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). This causes discontinuities in the data for two reasons. First, if households report their firm size precisely, employers with exactly 100 employees would be reclassified from large to small between waves 10 and 11. Second, more choices may lead workers to reconsider their estimates of firm/establishment sizes. The former explanation would manifest as a temporary increase in the number of reclassifications of the same employer from large to small between waves 10 and 11 but we would expect the share of reclassifications to return to its pre-change level between waves 11 and 12.

The solid line in figure (8) plots the share of workers who have the same employer across adjacent months over survey waves but report their employer size differently across waves. The number of employer size changes spikes in wave 11, consistent with the switch to the new classification system. It dips slightly in wave 12 but remains significantly elevated relative to its pre-change trend. Thus, although some of the change may have been due to reclassification of 100-employee firms, the vast majority seems to be inconsistencies in how workers report their employer size. One might worry that some other change happened between waves 10 and 11 that caused workers to be more likely to report changing employers. Thus the share of reclassifications could look elevated if the denominator is smaller. The dashed line in figure (8) shows that this does not appear to be the case, as the share of workers who stay with the same employer is similar across waves.

Figure 8: Reclassifications of firm size by survey wave.



Workers are classified as having the same job if they report working for the same employer number in reference month 4 of wave $t-1$ and reference month 1 of wave t. Of those who have the same job, size changes are defined as workers who classify employer x as a small firm in wave $t-1$ and a large firm in wave t or vice versa.

A.2. Additional background information

To evaluate how much of the employment gaps by race are attributable to worker characteristics, I fit the following linear probability model,

$$E_{irt} = \alpha_{rt} + \beta_{rt} X_{irt} + \epsilon_{irt}, \tag{36}$$

where E_{irt} is an indicator equal to 1 if person i of race r in month t is employed, α_{rt} are race by time fixed effects, X_{irt} includes a quadratic in age interacted with gender, martial status interacted with gender, typical occupation, typical industry, state, and metro area size. The coefficients on worker characteristics, β_{rt}, are estimated separately by race and time.

Using these estimates, I predict the employment rate for each race with respect to the white population as in a Oaxaca-Blinder decomposition,

$$\hat{E}_{irt} = \hat{\alpha}_{wt} + \hat{\beta}_{wt} X_{irt}. \tag{37}$$

Then, I construct the raw and conditional gaps,

$$\text{gap}_{rt}^{raw} = \frac{1}{N_r}\sum_{i}^{N_r} E_{irt} - \frac{1}{N_w}\sum_{i}^{N_w} E_{iwt}, \tag{38}$$

$$\text{gap}_{rt}^{cond} = \frac{1}{N_r}\sum_{i}^{N_r} E_{irt} - \hat{E}_{irt}. \tag{39}$$

For the estimation and constructing the gaps, I use the sample weights provided by the CPS. If the Black-white employment gap were fully explained by differences in industry exposure, age, geography, etc., then the conditional gap should be zero. Figure 1 shows that this is not the case. Table 13 reports the means, standard deviations, and correlations with the headline unemployment rate for each series.

Table 13: Employment gap summary statistics

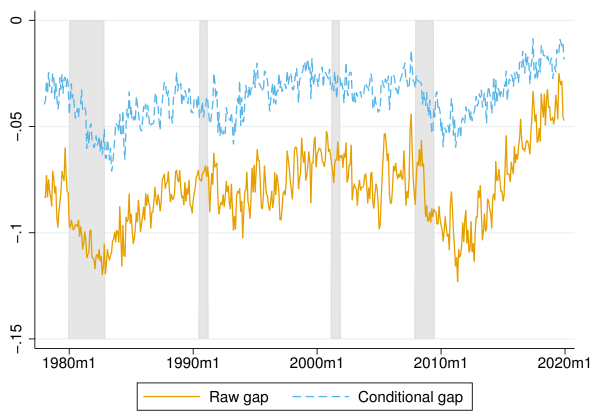
	Raw gap			**Conditional gap**		
	Mean	SD	Corr w/ UR	Mean	SD	Corr w/ UR
Both genders						
Black	-0.039	0.016	-0.799	-0.031	0.009	-0.813
Hispanic	0.010	0.024	-0.455	-0.009	0.007	-0.498
Men						
Black	-0.080	0.018	-0.801	-0.036	0.011	-0.815
Hispanic	0.053	0.027	-0.512	-0.007	0.011	-0.427
Women						
Black	0.004	0.017	-0.648	-0.026	0.008	-0.681
Hispanic	-0.038	0.024	-0.285	-0.011	0.006	-0.427

Source: CPS.
The table reports the mean, standard deviation, and correlation with the headline unemployment rate for the raw and conditional gaps in employment to population ratios relative to the white population, as defined in equations (38)-(39).

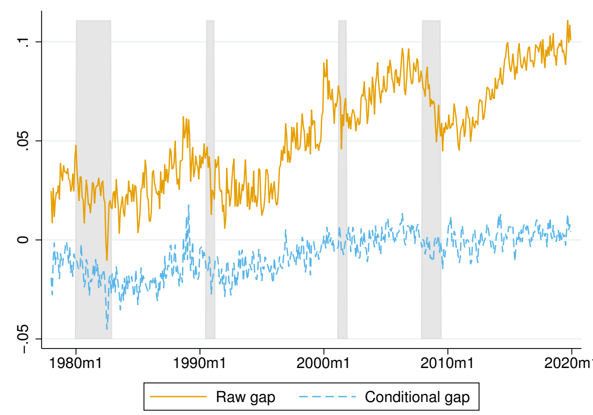
Next, I perform the same analysis by gender, where I estimate equations (36)-(39) separately for men and women. Figure 9 reports the same series separately by gender. Again, Table 13 reports summary statistics. The raw employment gaps are quite different across groups. Black men face persistently lower employment relative to white men, whereas Hispanic men have persistently higher employment. Black women tend to have higher employment than white women on average, although notably this pattern tends to reverse around recessions. Hispanic women generally have lower employment than white women. Across all groups, the mean conditional gap, reported in Table 13 is negative, indicating that even for the groups with positive average employment gaps, these gaps should be even more positive after adjusting for worker characteristics, industries, and occupations. Across all groups, both the raw gap and the conditional gap are negatively correlated with the headline unemployment. The gaps for Black men are the most strongly correlated.

Figure 9: Employment to population gap relative to white population

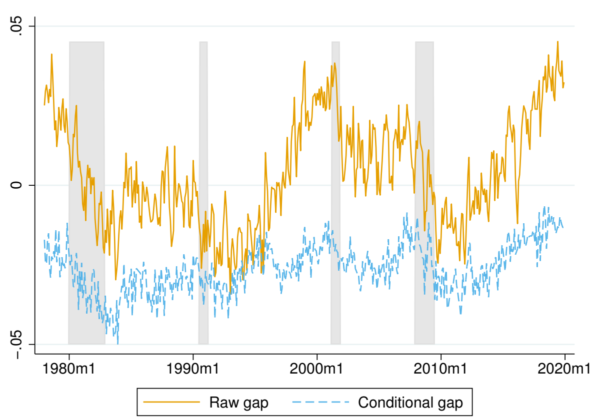
(a) Black men



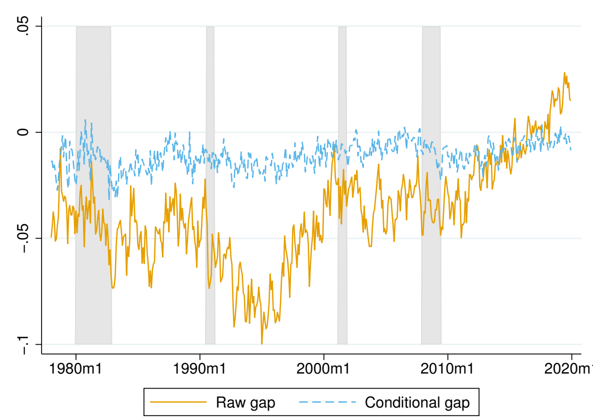
(b) Hispanic men



(c) Black women



(d) Hispanic women



Source: CPS.
The solid (Raw gap) lines plot the gap in the employment to population ratio for the Black and Hispanic populations relative to the white population, separately by gender. Panels (a) and (b) compare Black and Hispanic men to white men. Panels (c) and (d) compare Black and Hispanic women to white women. The dashed (Conditional gap) line plots the within-month employment gap, conditional on an age quadratic, marital status, occupation, industry, state, and metro area size. Table 13 reports the means, standard deviations, and correlations with the headline unemployment rate for each series.

I also report results in logs for each race and race by gender group,

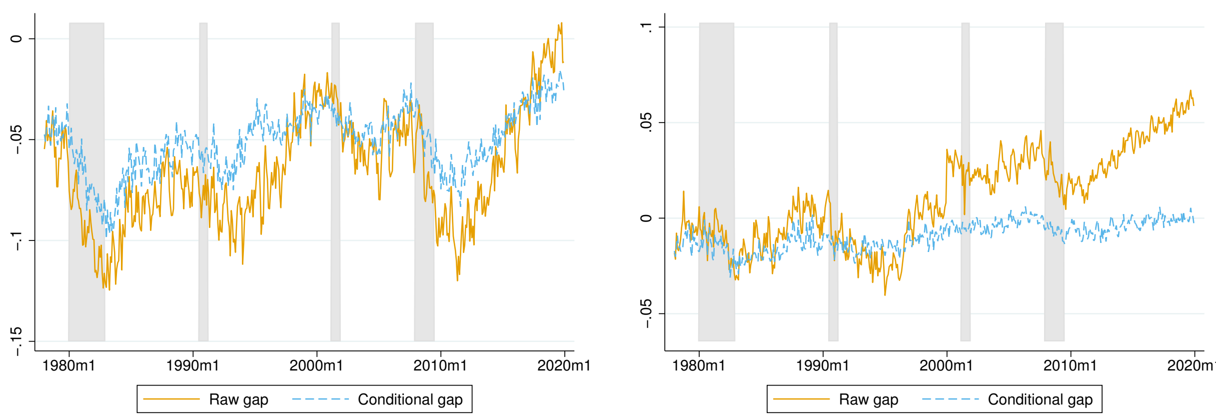
$$\log \text{gap}_{rt}^{raw} = \log\left(\frac{1}{N_r}\sum_{i}^{N_r} E_{irt}\right) - \log\left(\frac{1}{N_w}\sum_{i}^{N_w} E_{iwt}\right), \tag{40}$$

$$\log \text{gap}_{rt}^{cond} = \log\left(\frac{1}{N_r}\sum_{i}^{N_r} E_{irt}\right) - \log\left(\frac{1}{N_r}\sum_{i}^{N_r} \hat{E}_{irt}\right). \tag{41}$$

The results are shown in Figures 10 and 11, with summary statistics in Table 14. The patterns are similar in both levels and logs.

Figure 10: Employment to population gap relative to white

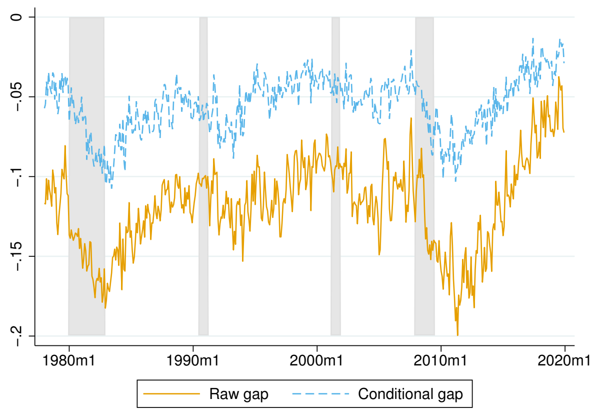
(a) Black **(b)** Hispanic



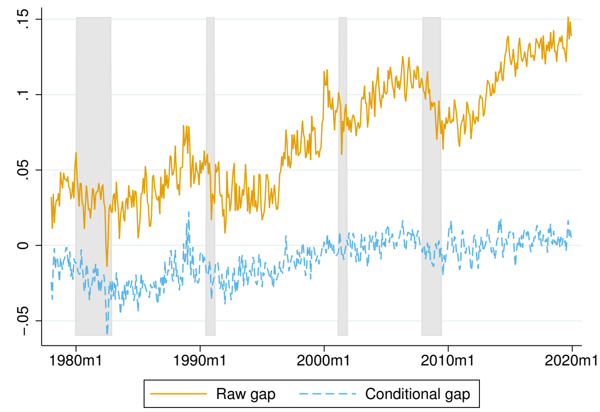
Source: CPS.
The solid (Raw gap) line plots the gap in the employment to population ratio for the Black and Hispanic populations relative to the white population in logs. The dashed (Conditional gap) line plots the within-month employment gap, conditional on an age quadratic by gender, marital status by gender, occupation, industry, state, and metro area size. Means, standard deviations, and correlations with the headline unemployment rate are reported in Table 14.

Figure 11: Employment to population gap relative to white population

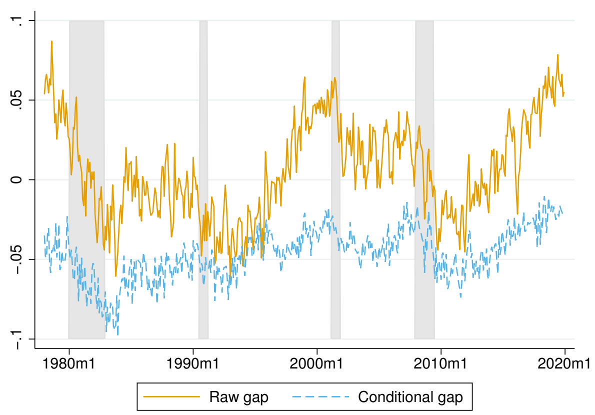
(a) Black men



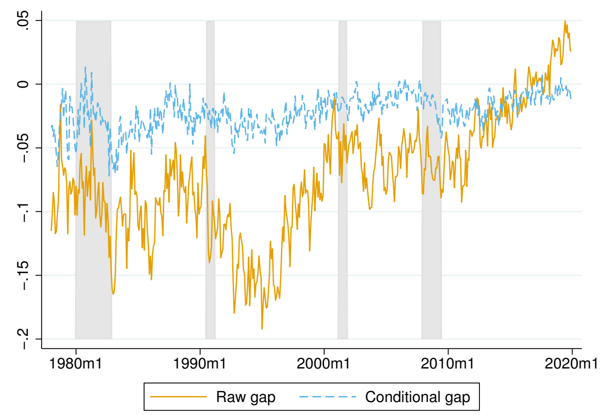
(b) Hispanic men



(c) Black women



(d) Hispanic women



Source: CPS.
The solid (Raw gap) lines plot the log gap in the employment to population ratios, defined in equation 40, for the Black and Hispanic populations relative to the white population, separately by gender. Panels (a) and (b) compare Black and Hispanic men to white men. Panels (c) and (d) compare Black and Hispanic women to white women. The dashed (Conditional gap) line plots the within-month employment gap, defined in equation 41, conditional on an age quadratic, marital status, occupation, industry, state, and metro area size. Table 14 reports the means, standard deviations, and correlations with the headline unemployment rate for each series.

Table 14: Log employment gap summary statistics

	Raw gap			Conditional gap		
	Mean	SD	Corr w/ UR	Mean	SD	Corr w/ UR
Both genders						
Black	-0.065	0.027	-0.863	-0.051	0.016	-0.861
Hispanic	0.016	0.038	-0.497	-0.014	0.012	-0.541
Men						
Black	-0.118	0.028	-0.847	-0.055	0.018	-0.854
Hispanic	0.071	0.037	-0.518	-0.009	0.014	-0.461
Women						
Black	0.006	0.030	-0.670	-0.046	0.016	-0.745
Hispanic	-0.073	0.047	-0.384	-0.022	0.014	-0.464

Source: CPS.
The table reports the mean, standard deviation, and correlation with the headline unemployment rate for the raw and conditional gaps in employment to population ratios relative to the white population, as defined in equations (40)-(41).

Table 15 shows that the patterns over employer composition are broadly consistent between the SIPP and the CPS and across different definitions of firm size. Panel (a) reports the raw and conditional gaps in the probability of working for a large firm, relative to white workers. Black workers are 8 percentage points more likely to work for a large firm as measured by the SIPP, 6.8 percentage points measured by the CPS and 6.2 percentage points when the threshold is raised to 500 or more employees. The estimates are reasonably similar across sources, with the SIPP tending to overestimate the propensity of Black workers to sort to large firms and underestimate the propensity for Hispanic workers to sort to small firms, relative to the CPS.

Table 15: Employer composition comparison across sources

	Raw gap			Conditional gap		
	SIPP	CPS	CPS	SIPP	CPS	CPS
(a) Large	100+	100+	500+	100+	100+	500+
Black	8.015	6.782	6.237	7.061	6.690	6.196
	(0.390)	(0.120)	(0.117)	(0.0721)	(0.122)	(0.120)
Hispanic	-0.780	-3.066	-3.905	-0.392	-1.435	-1.951
	(0.392)	(0.0989)	(0.0920)	(0.0799)	(0.114)	(0.108)
(b) Small						
Black	-7.400	-5.664	-5.119	-8.544	-6.943	-6.448
	(0.301)	(0.104)	(0.116)	(0.0630)	(0.109)	(0.120)
Hispanic	9.065	11.63	12.47	0.911	3.383	3.899
	(0.367)	(0.0973)	(0.0997)	(0.0762)	(0.111)	(0.115)

B. Additional empirical results

B.1. Results by gender

Table 2 reports the baseline results for how employer type-specific separation and job-finding rates vary by race and with aggregate conditions. Tables 16 and 17 report the results for men and women, respectively. Comparing Panel (a) across the two tables, the increase in separations during high unemployment months is particularly strong for men. The increase in separation rates during these months is similar for Black and white men. Comparing Panel (b) across the two tables, both genders experience a strong decrease in job-finding rates during high unemployment months. The result that Black workers in particular face lower job-finding rates and that this is driven by large firms is stronger among women than men.

Table 16: Transition rates by race and aggregate unemployment, men

(a) Separations: E to N	(1) All	(2) Large	(3) Small	(4) Government	(5) Self
Black	0.08	0.06	0.31	-0.28	-0.02
	(0.04)	(0.06)	(0.10)	(0.06)	(0.08)
High UR	0.14	0.12	0.28	0.17	0.03
	(0.05)	(0.06)	(0.09)	(0.07)	(0.04)
Black × High UR	0.01	0.12	-0.25	0.07	0.28
	(0.07)	(0.10)	(0.22)	(0.13)	(0.16)
N	1,900,483	1,900,483			
R^2	0.01	0.01			
Black mean	1.52	1.55	2.19	0.71	0.65
White mean	1.17	1.14	1.75	0.79	0.35

(b) Job-finding: N to E	(1) All	(2) Large	(3) Small	(4) Government	(5) Self
Black	-1.30	-0.33	-0.84	-0.00	-0.11
	(0.09)	(0.06)	(0.05)	(0.02)	(0.02)
High UR	-0.77	-0.33	-0.28	-0.02	-0.06
	(0.11)	(0.05)	(0.05)	(0.02)	(0.01)
Black × High UR	-0.10	-0.11	0.04	-0.04	0.03
	(0.14)	(0.10)	(0.07)	(0.04)	(0.03)
N	837,928	837,928	837,928	837,928	837,928
R^2	0.05	0.02	0.02	0.00	0.00
Black mean	2.81	1.45	0.85	0.23	0.12
White mean	3.01	1.31	1.17	0.23	0.17

The table reports differences in employer-type specific separation and job-finding rates by race and macroeconomic conditions for men. The units are percentage points. Panel (a) reports the estimates for aggregate separations rates from equation (1) in column (1) and the interacted coefficients with employer type from equation (3) in columns (2)-(5). Panel (b) reports the estimates for aggregate job-finding rates from equation (2) in column (1) and the estimates for equation (4) with an outcome variable for each employer type in columns (2)-(5). All specifications include controls for age, age-squared, and marital status; education; geographic region; metro area size; calendar month fixed effects. Panel (a) includes controls for industry; occupation; and length of employment spell in years. Panel (b) includes controls for length of nonemployment spell in years; indicator for new entrants; and indicator for unobserved full length of nonemployment spell. Standard errors are clustered by month.

Table 17: Transition rates by race and aggregate unemployment, women

(a) Separations: E to N	(1) All	(2) Large	(3) Small	(4) Government	(5) Self
Black	0.08	0.25	0.21	-0.33	0.07
	(0.04)	(0.06)	(0.09)	(0.06)	(0.13)
High UR	-0.04	0.02	-0.08	-0.02	-0.09
	(0.04)	(0.05)	(0.06)	(0.10)	(0.06)
Black × High UR	-0.13	-0.28	-0.13	0.07	0.31
	(0.07)	(0.11)	(0.16)	(0.12)	(0.26)
N	1,800,752	1,800,752	1,800,752	1,800,752	1,800,752
R2	0.01	0.01	0.01	0.01	0.01
Black mean	1.66	1.81	2.20	0.88	1.09
White mean	1.44	1.42	1.83	1.09	0.70

(b) Job-finding: N to E	(1) All	(2) Large	(3) Small	(4) Government	(5) Self
Black	-0.36	0.12	-0.41	0.01	-0.06
	(0.07)	(0.05)	(0.03)	(0.02)	(0.01)
High UR	-0.53	-0.21	-0.18	-0.05	-0.03
	(0.07)	(0.03)	(0.03)	(0.02)	(0.01)
Black × High UR	-0.29	-0.31	0.05	-0.03	0.02
	(0.10)	(0.07)	(0.04)	(0.03)	(0.02)
N	1,388,861	1,388,861	1,388,861	1,388,861	1,388,861
R2	0.04	0.02	0.01	0.01	0.00
Black mean	2.53	1.40	0.66	0.31	0.07
White mean	2.01	0.85	0.68	0.27	0.10

The table reports differences in employer-type specific separation and job-finding rates by race and macroeconomic conditions for women. The units are percentage points. Panel (a) reports the estimates for aggregate separations rates from equation (1) in column (1) and the interacted coefficients with employer type from equation (3) in columns (2)-(5). Panel (b) reports the estimates for aggregate job-finding rates from equation (2) in column (1) and the estimates for equation (4) with an outcome variable for each employer type in columns (2)-(5). All specifications include controls for age, age-squared, and marital status; education; geographic region; metro area size; calendar month fixed effects. Panel (a) includes controls for industry; occupation; and length of employment spell in years. Panel (b) includes controls for length of nonemployment spell in years; indicator for new entrants; and indicator for unobserved full length of nonemployment spell. Standard errors are clustered by month.

Table 18: Separation rate heterogeneity, men

	(1) All	(2) Voluntary	(3) Involuntary
Large	-0.03	-0.02	-0.16
	(0.06)	(0.10)	(0.09)
Small × Black	-0.17	-0.93	0.36
	(0.18)	(0.25)	(0.24)
Large × Black	0.03	-0.42	0.38
	(0.07)	(0.12)	(0.09)
Small × HighUR	0.01	-0.88	1.21
	(0.10)	(0.14)	(0.15)
Large × HighUR	-0.22	-0.84	0.62
	(0.05)	(0.07)	(0.06)
Small × Black × HighUR	-0.13	-0.10	-0.11
	(0.31)	(0.40)	(0.49)
Large × Black × HighUR	-0.19	-0.26	-0.05
	(0.12)	(0.17)	(0.16)
N	1,276,825	1,269,010	1,269,010
R^2	0.02	0.02	0.02
Black mean	2.29	2.05	2.08
White mean	2.06	2.28	1.60

The table reports differences in size-specific and reason-specific separation rates by race and macroeconomic conditions given by equation (9) for men. The units are percentage points. The sample includes all workers who report a job at a large or small firm. The outcome variable in column (1) is an indicator equal to 1 if the worker reports the job ending that month. The outcome variables in columns (2)-(3) are indicators equal to 1 if the worker reports the job ending and gives an involuntary or voluntary reason for it, respectively. All specifications include controls for age, age-squared, and marital status interacted with gender; education; geographic region; metro area size; calendar month fixed effects; job tenure in years; log wage; hours; union membership; and industry. Standard errors are clustered by month.

Table 19: Separation rate heterogeneity, women

	(1) All	(2) Voluntary	(3) Involuntary
Large	-0.12	-0.11	0.06
	(0.06)	(0.10)	(0.07)
Small × Black	0.09	-0.45	0.77
	(0.17)	(0.25)	(0.20)
Large × Black	-0.00	-0.46	0.36
	(0.07)	(0.12)	(0.09)
Small × HighUR	-0.53	-1.13	0.61
	(0.10)	(0.14)	(0.11)
Large × HighUR	-0.22	-0.83	0.61
	(0.05)	(0.07)	(0.06)
Small × Black × HighUR	-0.04	-0.05	0.01
	(0.27)	(0.39)	(0.38)
Large × Black × HighUR	-0.19	-0.26	-0.05
	(0.12)	(0.17)	(0.16)
N	1,295,415	1,287,197	1,287,197
R^2	0.02	0.02	0.01
Black mean	2.46	2.51	1.81
White mean	2.24	2.54	1.34

The table reports differences in size-specific and reason-specific separation rates by race and macroeconomic conditions given by equation (9) for women. The units are percentage points. The sample includes all workers who report a job at a large or small firm. The outcome variable in column (1) is an indicator equal to 1 if the worker reports the job ending that month. The outcome variables in columns (2)-(3) are indicators equal to 1 if the worker reports the job ending and gives an involuntary or voluntary reason for it, respectively. All specifications include controls for age, age-squared, and marital status interacted with gender; education; geographic region; metro area size; calendar month fixed effects; job tenure in years; log wage; hours; union membership; and industry. Standard errors are clustered by month.

B.2. Alternative measures of aggregate conditions

The results reported in Section 3 compare the transition rates of Black and white workers in high unemployment periods, defined as months in which the gap between the headline unemployment rate and its time-varying noncyclical rate are in the top tercile of all months. Table 20 shows that the results are similar using the continuous unemployment gap rather than the indicator for high unemployment months. Table 21 shows similar results with the continuous state-level unemployment rate.

Table 20: Transition rates by race and unemployment deviations from trend

(a) Separations: E to N	(1) All	(2) Large	(3) Small	(4) Government	(5) Self
Black	0.07	0.14	0.21	-0.29	0.10
	(0.02)	(0.04)	(0.06)	(0.04)	(0.06)
UR gap	0.02	0.02	0.03	0.03	0.00
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Black × UR gap	-0.02	-0.03	-0.04	0.01	0.08
	(0.01)	(0.02)	(0.03)	(0.02)	(0.03)
N	3,701,235	3,701,235	3,701,235	3,701,235	3,701,235
R2	0.01	0.01	0.01	0.01	0.01
Black mean	1.60	1.69	2.20	0.82	0.82
White mean	1.30	1.27	1.79	0.96	0.47

(b) Job-finding: N to E	(1) All	(2) Large	(3) Small	(4) Government	(5) Self
Black	-0.82	-0.14	-0.58	-0.00	-0.07
	(0.05)	(0.03)	(0.03)	(0.01)	(0.01)
UR gap	-0.17	-0.07	-0.06	-0.01	-0.01
	(0.02)	(0.01)	(0.01)	(0.00)	(0.00)
Black × UR gap	-0.05	-0.06	0.01	-0.01	0.01
	(0.02)	(0.01)	(0.01)	(0.01)	(0.00)
N	2,226,789	2,226,789	2,226,789	2,226,789	2,226,789
R2	0.04	0.02	0.02	0.01	0.00
Black mean	2.65	1.42	0.74	0.28	0.09
White mean	2.39	1.03	0.87	0.26	0.13

The table reports differences in employer-type specific separation and job-finding rates by race and macroeconomic conditions. The units are percentage points. UR gap is the demeaned unemployment rate deviations from trend. Panel (a) reports the estimates for aggregate separations rates from equation (1) in column (1) and the interacted coefficients with employer type from equation (3) in columns (2)-(5). Panel (b) reports the estimates for aggregate job-finding rates from equation (2) in column (1) and the estimates for equation (4) with an outcome variable for each employer type in columns (2)-(5). All specifications include controls for age, age-squared, and marital status interacted with gender; education; geographic region; metro area size; calendar month fixed effects. Panel (a) includes controls for industry; occupation; and length of employment spell in years. Panel (b) includes controls for length of nonemployment spell in years; indicator for new entrants; and indicator for unobserved full length of nonemployment spell. Standard errors are clustered by month.

Table 21: Transition rates by race and state-level unemployment

(a) Separations: E to N	(1) All	(2) Large	(3) Small	(4) Government	(5) Self
Black	0.07	0.14	0.21	-0.29	0.09
	(0.02)	(0.04)	(0.06)	(0.04)	(0.06)
State UR	0.03	0.02	0.05	0.03	-0.01
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Black × State UR	-0.01	-0.02	-0.04	0.00	0.06
	(0.01)	(0.02)	(0.03)	(0.02)	(0.03)
N	3,701,235	3,701,235	3,701,235	3,701,235	3,701,235
R2	0.01	0.01	0.01	0.01	0.01
Black mean	1.60	1.69	2.20	0.82	0.82
White mean	1.30	1.27	1.79	0.96	0.47

(b) Job-finding: N to E	(1) All	(2) Large	(3) Small	(4) Government	(5) Self
Black	-0.79	-0.13	-0.57	0.00	-0.07
	(0.05)	(0.03)	(0.03)	(0.01)	(0.01)
State UR	-0.15	-0.07	-0.05	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
Black × State UR	-0.05	-0.05	0.00	-0.01	0.01
	(0.02)	(0.01)	(0.01)	(0.01)	(0.00)
N	2,226,789	2,226,789	2,226,789	2,226,789	2,226,789
R2	0.04	0.02	0.02	0.01	0.00
Black mean	2.65	1.42	0.74	0.28	0.09
White mean	2.39	1.03	0.87	0.26	0.13

The table reports differences in employer-type specific separation and job-finding rates by race and macroeconomic conditions. The units are percentage points. State UR is the demeaned state-level unemployment rate. Panel (a) reports the estimates for aggregate separations rates from equation (1) in column (1) and the interacted coefficients with employer type from equation (3) in columns (2)-(5). Panel (b) reports the estimates for aggregate job-finding rates from equation (2) in column (1) and the estimates for equation (4) with an outcome variable for each employer type in columns (2)-(5). All specifications include controls for age, age-squared, and marital status interacted with gender; education; geographic region; metro area size; calendar month fixed effects. Panel (a) includes controls for industry; occupation; and length of employment spell in years. Panel (b) includes controls for length of nonemployment spell in years; indicator for new entrants; and indicator for unobserved full length of nonemployment spell. Standard errors are clustered by month.

C. Wage setting details

C.1. Bargaining with groups

Suppose the firm can observe the worker's group (g) and new hire status at the time of bargaining. The firm's value at the time of bargaining is given by

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

where $\tilde{n}_g = (1-\delta)n_g$ is the number of non-separated workers from group g from the previous period and $h_g = \frac{u_{gt}}{u_t} v q(\theta_t)(1 - F(x_g|p(g,z)))$ is the number of hires from group g. The last line shows the mapping back to the law of motion in equation (13).

To relate the firm value at bargaining back to the firm's problem from the main text, notice that vacancies can be rewritten as[8]

$$
v = \sum_g \frac{h_g}{q(\theta_t)(1 - F(x_g|p(g,z)))}
$$

Then using this expression, the firm's problem from equation (11) can be equivalently expressed as

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

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

[8] The omitted step is
$v = \frac{h_g}{\frac{u_{gt}}{u_t} q(\theta_t)(1-F(x_g|p(g,z)))} = \frac{u_{Bt}}{u_t} \frac{h_B}{\frac{u_{Bt}}{u_t} q(\theta_t)(1-F(x_B|p(B,z)))} + \frac{u_{Wt}}{u_t} \frac{h_W}{\frac{u_{Wt}}{u_t} q(\theta_t)(1-F(x_W|p(W,z)))}$

D_{t,h_g}, where the arguments of $D()$ are omitted to ease notation.

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

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

$$
\begin{aligned}
V^n_t(g,z) - V^u_t(g) =& w^n_t(n',z,g) - (b + \Omega_t(g)) + \beta(1-\delta)\mathbb{E}_t \left[V^n_{t+1}(g,z) - V^u_{t+1}(g)\right] \\
V^h_t(g,z) - V^u_t(g) =& w^h_t(\hat{x}_g,n',z,g) - (b + \Omega_t(g)) + \beta(1-\delta)\hat{x}_g(z)\mathbb{E}_t \left[V^n_{t+1}(g,z) - V^u_{t+1}(g)\right]
\end{aligned}
$$

Using the bargaining rules defined in equations (24) and (25),

$$
\begin{aligned}
w^n(n',z,g) =& \phi\alpha a_t z(n')^{\alpha-1} - \phi \sum_k \Big(\tilde{n}_k w^n_{n'}(n',z,k) + h_k w^h_{n'}(\hat{x}_k,n',z,k)\Big) + (1-\phi)(b+\Omega_t(g)) \\
w^h(\hat{x}_g,n',z,g) =& \hat{x}_g \phi\alpha a_t z(n')^{\alpha-1} \\
&- \hat{x}_g \phi \sum_k \Big(\tilde{n}_k w^n_{n'}(n',z,k) + h_k w^h_{n'}(\hat{x}_k,n',z,k)\Big) + (1-\phi)(b+\Omega_t(g))
\end{aligned}
$$

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

$$
w^h(\hat{x}_g,n',z,g) = \hat{x}_g w^n(n',z,g) + (1-\hat{x}_g)(1-\phi)(b+\Omega_t(g))
$$

which implies

$$
w^h_{n'}(x_g,n',z,g) = \hat{x}_g w^n_{n'}(n',z,g)
$$

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

$$
w^n(n',z,B) - w^n(n',z,W) = (1-\phi)(\Omega_t(W) - \Omega_t(B))
$$

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

$$w^n(n', z, g) = \phi a_t z(n')^{\alpha-1} - \phi n' w^n_{n'}(n', z, g) + (1-\phi)(b + \Omega_t(g))$$

Solving this differential equation gives the following equilibrium wages

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

C.2. Bargaining without observing groups

Now suppose the firm cannot observe the group of the individual workers they are bargaining with, but they do know the relative shares and hiring thresholds. The firm's value at the time of bargaining is given by

$$\begin{aligned} D_t(\tilde{n}, h, \{x_g\}, \lambda^n_g, \lambda^h_g, z) =& a_t z(n')^{\alpha} - \tilde{n} w^n(n', z) - h w^h(\hat{x}, n', z) + \beta \mathbb{E}_t J_{t+1}(\lambda'_B n', \lambda'_W n', z) \\ & \text{s.t.} \\ & n' = \tilde{n} + h\hat{x} \\ & \lambda'_g n' = \underbrace{\lambda^n_g \tilde{n}}_{\text{composition existing}} + \underbrace{\lambda^h_g h \hat{x}(x_g, p(g, z))}_{\text{composition new hires}} \end{aligned}$$

where λ^n_g is the share of workers from group g that continued from the previous period and λ^h_g is the share of new hires from group g.

As before, we can relate the firm value at bargaining back to the firm's problem,

$$\begin{aligned} J_t(\lambda_B n, \lambda_W n, z) = \max_{h, \lambda_h, x_B, x_W} & - \sum_g \frac{c_v \lambda_h h}{q(\theta_t)(1 - F(x_g | p(g, z)))} \\ & + D_t((1-\delta)n, h, \hat{x}(x_B, x_W), \lambda^n_g, \lambda^h_g(x_B, x_W), z) \end{aligned}$$

where

$$J_{t,n}(n_B, n_W, z) = \lambda_B J_{t,n_B}(n_B, n_W, z) + \lambda_W J_{t,n_W}(n_B, n_W, z) = (1-\delta) D_{t,\tilde{n}}(\tilde{n}, h, \hat{x}, \lambda^n_g, \lambda^h_g, z)$$

Taking the marginal surplus with respect to a continuing worker ($\tilde{n}$) or a new hire (h),

$$\begin{aligned} D_{t,\tilde{n}} =& a_t z(n')^{\alpha-1} - w^n(n',z) - \left(\tilde{n} w^n_{n'}(n',z) + h w^h_{n'}(\hat{x},n',z)\right) + \beta(1-\delta)\mathbb{E}_t D_{t+1,\tilde{n}} \\ D_{t,h} =& \hat{x} a_t z(n')^{\alpha-1} - w^h(\hat{x},n',z) - \hat{x}\left(\tilde{n} w^n_{n'}(n',z) + h w^h_{n'}(\hat{x},n',z)\right) + \hat{x}\beta(1-\delta)\mathbb{E}_t D_{t+1,\tilde{n}} \end{aligned}$$

The marginal surplus on the worker's side depends on the composition of workers the firm is bargaining with,

$$\begin{aligned} \sum_g \lambda^n_g \Big(V^n_t(g,z) - V^u_t(g)\Big) =& w^n_t(n',z) - \sum_g \lambda^n_g \Big((b+\Omega_t(g)) + \beta(1-\delta)\mathbb{E}_t\left[V^e_{t+1}(g,z) - V^u_{t+1}(g)\right]\Big) \\ \sum_g \lambda^h_g \Big(V^h_t(g,z) - V^u_t(g)\Big) =& w^h_t(\hat{x},n',z) \\ & - \sum_g \lambda^h_g \Big((b+\Omega_t(g)) + \beta(1-\delta)\hat{x}(x_g,p(g,z))\mathbb{E}_t\left[V^e_{t+1}(g,z) - V^u_{t+1}(g)\right]\Big) \end{aligned}$$

Using the bargaining rules defined in equations (24) and (25),

$$\begin{aligned} w^n(n',z) =& \phi a_t z(n')^{\alpha-1} - \phi\left(\tilde{n} w^n_{n'}(n',z) + h w^h_{n'}(\hat{x},n',z)\right) + (1-\phi)\left(b + \sum_g \lambda^n_g \Omega_t(g)\right) \\ w^h(\hat{x},n',z) =& \hat{x}\phi a_t z(n')^{\alpha-1} - \hat{x}\phi\left(\tilde{n} w^n_{n'}(n',z) + h w^h_{n'}(\hat{x},n',z)\right) + (1-\phi)\left(b + \sum_g \lambda^h_g \Omega_t(g)\right) \end{aligned}$$

and we get the following wage equations

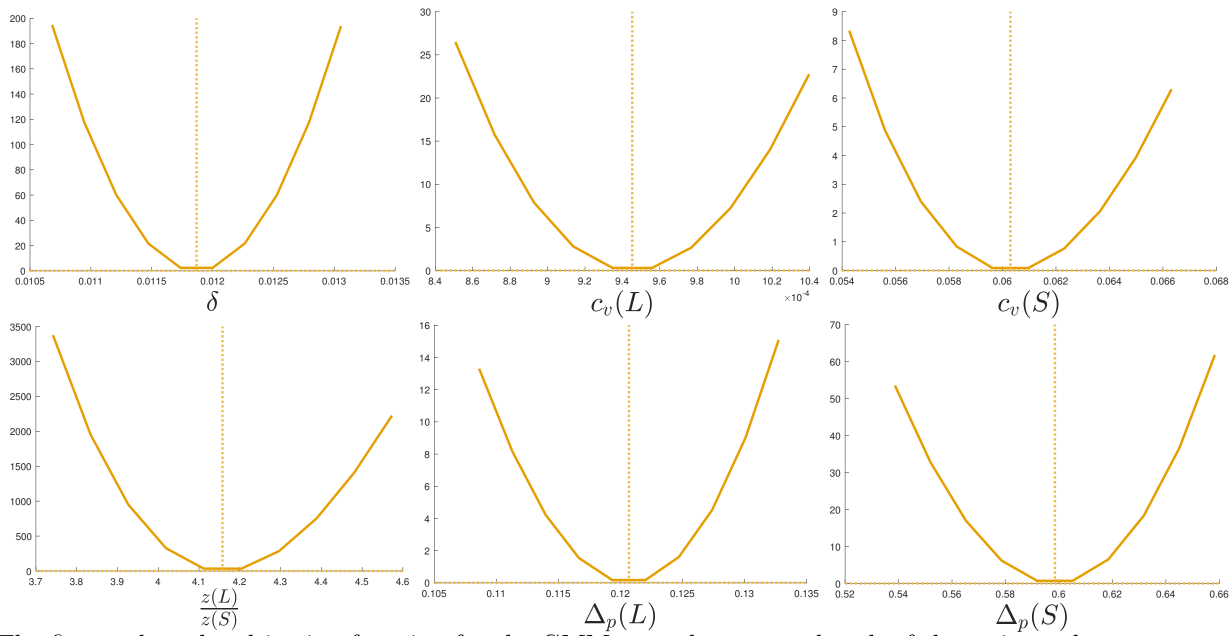
$$\begin{aligned} w^n(n',z,\lambda^n) =& \frac{\alpha\phi}{1-\phi+\alpha\phi} a_t z(n')^{\alpha-1} + (1-\phi)\left(b + \sum_g \lambda^n_g \Omega_t(g)\right) \\ w^h(\hat{x}_g,n',z,\lambda^h) =& \left(\sum_g \lambda^h_g \hat{x}(x_g,p(g,z))\right) \frac{\alpha\phi}{1-\phi+\alpha\phi} a_t z(n')^{\alpha-1} + (1-\phi)\left(b + \sum_g \lambda^h_g \Omega_t(g)\right) \end{aligned}$$

From the perspective of the firm, the wage bill is the same whether they can observe the group of the worker or not, as long as the wages satisfy the participation constraint for all groups. However, in this case the distribution of wages across workers changes and this will have consequences for the workers' outside options, $\Omega_t(g)$.

D. Identification

Section 5 describes the intuition for the identification of the six estimated parameters. Figure 12 shows that the objective function reaches a local minimum around each parameter value. The objective function uses the inverse of the variance-covariance matrix obtained from the block bootstrap described in Section 3.5 with 1,000 iterations.

Figure 12: Objective function minimization



The figure plots the objection function for the GMM procedure around each of the estimated parameters. The weight matrix is the inverse of the variance covariance matrix obtained with a block bootstrap by individual within each SIPP panel.