Firm Heterogeneity and Racial Labor Market Disparities*

Caitlin Hegarty

University of Michigan

October 27, 2022

Click here for latest version

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 practices. There are persistent differences in the hiring rates of Black and white workers across firms of different sizes. In an empirical decomposition, the behavior of small firms appears to contribute most to the *average* racial employment gap. Meanwhile, the change in the hiring gap at large firms contributes most to the *variation* in the racial employment gap over the business cycle. 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. This can produce larger changes in hiring rates for the disadvantaged workers at firms with better screening technology.

Keywords:

*Caitlin Hegarty (hegartyc@umich.edu): University of Michigan, Department of Economics. This material is based upon work supported by the National Science Foundation Graduate Research Fellowship Program under Grant No. DGE 1256260. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author and do not necessarily reflect the views of the National Science Foundation.

1. Introduction

The Black population in the U.S. faces persistently lower rates of employment than the white population. Additionally, Black employment tends to respond 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 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 higher unexplained differences in turnover of Black workers at small firms contribute most to the average racial employment gap, consistent with the fact that Black workers are more likely to be employed by large firms. Meanwhile, when the economy contracts, the reduction in hiring for Black workers at large firms is the strongest driver of the worsening employment gap. The second half of the paper develops a quantitative model to evaluate the role of information frictions and firm heterogeneity in explaining these empirical facts. The model predicts that the racial employment gap should worsen in response to aggregate shocks by allowing firms to be more selective about the workers they hire. This disproportionately affects minority workers, who face more severe information frictions in hiring.

First, I adapt a decomposition technique from the macro literature to quantify the contributions of differences in employer composition and firm-size specific transition rates to the racial employment gap both on average and over the business cycle. 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 employment to population ratio in the Survey of Income and Program Participation (SIPP) was 4.3 percentage points lower than the white ratio. Unexplained differences in turnover of Black workers at small firms contributed -21.3 basis points to the employment gap over this period. Meanwhile large firms contributed -9.1

basis points.

Applying the decomposition to the business cycle, fluctuations in hiring by large firms contribute most to the change in the racial employment gap. In my framework, a one percentage point increase in the headline unemployment rate is associated with a 1.3 basis point decrease in the Black employment rate relative to white. Decomposing this change into contributions of hiring and separations by firm type, the relative change in hiring at large firms explains 2.4 basis points of the decrease, overshooting the total effect. Meanwhile, the relative change in hiring at small firms contributes a positive 0.4 basis point, offsetting some of the large firm effect.

In Section 4, I develop a quantitative 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 cyclical fluctuations in the hiring gap. 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 means that within firms, the benefit to screening minority workers is lower than the benefit to screening majority workers. If the firm received only minority applicants, it would prefer a low selectivity strategy, whereas if it received only majority applicants, it would prefer a high selectivity strategy. Because the firm cannot target its vacancies to applicants of a particular group, it will choose a strategy in the middle, hiring fewer minority applicants (higher selectivity) and more majority applicants (lower selectivity) than it would in a separate equilibrium. This assumption on its own generates the steady state employment gap, and when paired with the first assumption it produces a higher share of minority employment at large firms.

Over the business cycle, the model predicts that the racial employment gap will worsen. A decrease in market tightness means that firms attract more applicants per unit of search intensity. Thus, the relative cost of the high selectivity strategy decreases. The difference in signal quality leads firms to increase selectivity for minority workers by more than majority workers, producing the pattern in the data that the hiring gap worsens over the business cycle.

Related literature

This paper is related 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 hiring margin is most important factor in cyclical employment gaps 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 under-representation 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 in a business cycle context and how it interacts with the firm size distribution. 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 is important across racial groups as well.

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 shows the business cycle implications. Section 7 concludes.

2. Background Empirical Facts

2.1. Data

Survey of Income and Program Participation (SIPP)

My primary data source will be 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 other main disadvantages of the SIPP are that the highest threshold available for defining large firms is 100 employees or more, which is low relative to the literature, and the survey design leads to small gaps between panels that make time-series analysis more complicated. I will 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 80k to 100k 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 analysis I will be focusing on individuals aged 20 or older who self-identify as non-Hispanic

[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.

white or Black.[2] This gives me a sample of about 286k 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 that 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 prioritize the job that is coded first and I only identify self-employed workers who 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 mistakes in the start/end dates.

Annual Social and Economic Supplement to the CPS (ASEC)

To supplement the analysis from the SIPP, I will also use the Annual Social and Economic Supplement to the CPS (ASEC), which provides a nice annual snapshot of employment and employer composition, but lacks the detailed transition dynamics from the SIPP. The

[2] The patterns in sorting among firms are very different for Hispanic workers. They tend to be more employed by small businesses relative to large than white workers, though almost all of this difference can be explained by differences in industry and other factors. I don't have enough power in the SIPP to reliably look at differences for other groups. Extensions to more racial and ethnic groups will be an important area for future research.

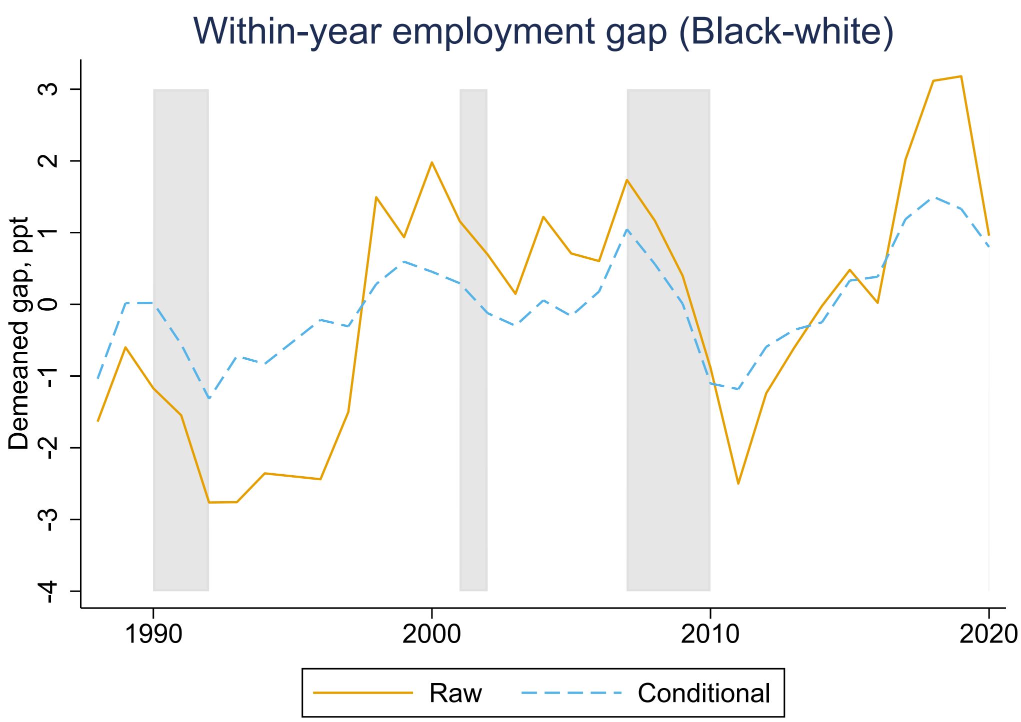
survey asks questions about all household members' current employment status, as well as more detailed questions about the main job they held in the previous year. This includes industry, occupation, earnings, and notably, firm size. My sample covers individuals aged 18-65 for calendar years 1987-2019. The sample size varies from about 75k to 115k adults per year.

I use the current employment status information in the next section to construct a smooth annual time series of the employment to population ratio by race. I choose to use the ASEC for this motivation because it does not have the same issues of gaps between panels and attrition that make the SIPP noisy to plot. I then use the backward-looking questions about the person's job over the previous year to construct a measure of the annual share of workers by employer type. Whereas my measure from the SIPP is the monthly employer composition, the ASEC captures the annual average of an individual's modal employer over the previous 12 months. I use this data primarily to validate the firm size measure from the SIPP, as well as explore sensitivity to higher thresholds for defining large firms and more detailed geographic controls than are available in the SIPP.

2.2. The unexplained gap in employment rates widens over the business cycle

First, I use data from the ASEC to show how the racial employment gap, defined as the Black minus white employment to population ratios, varies over the business cycle. A decrease in the employment gap means that Black workers are less likely to be employed than white workers. The solid line in Figure 1 shows the main pattern that the employment gap tends to worsen during recessions and improve during booms (relative to its mean). Some of the difference in employment rates can be explained by differences in occupation, industry, geography, but I show that the cyclical pattern cannot. The dashed line in Figure 1 shows the mean difference in residuals by race from regressing an employment indicator on a number of controls for individual characteristics separately for each year. If the Black employment rate tended to fall more during downturns because Black workers were more likely to work for volatile industries, then the cyclical pattern should disappear after controlling for year-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 employment gap and the annual average headline unemployment rate is -0.56 for the raw series and -0.64 for the conditional series. Both correlations have p-values below 0.001. Appendix A.2 replicates this pattern with the SIPP.

Figure 1: Racial employment gap over the business cycle

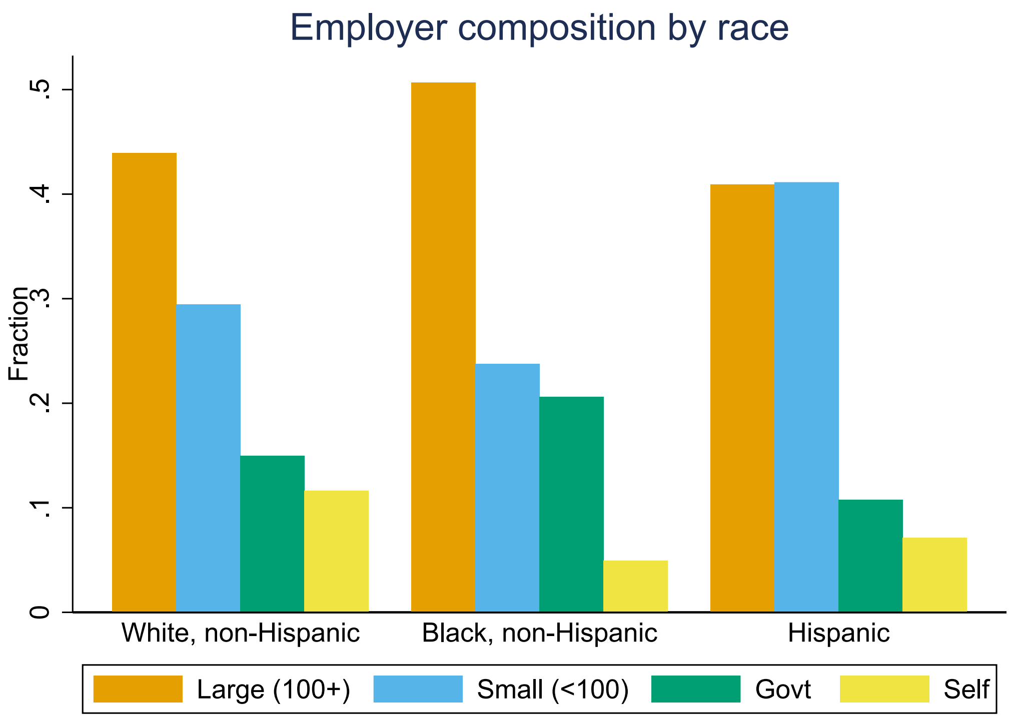


Source: ASEC supplement to the CPS.
The solid (Raw) line plots the demeaned employment gap between Black and white workers aged 18-65. The mean is -9.6 percentage points and standard deviation 1.7. The dashed (Conditional) line plots the demeaned within-year employment gap, conditional on age and education by gender, occupation, industry, state, and metro area size. The mean is -3.3 percentage points and standard deviation 0.7.

2.3. Black workers are more likely to be employed by large firms

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

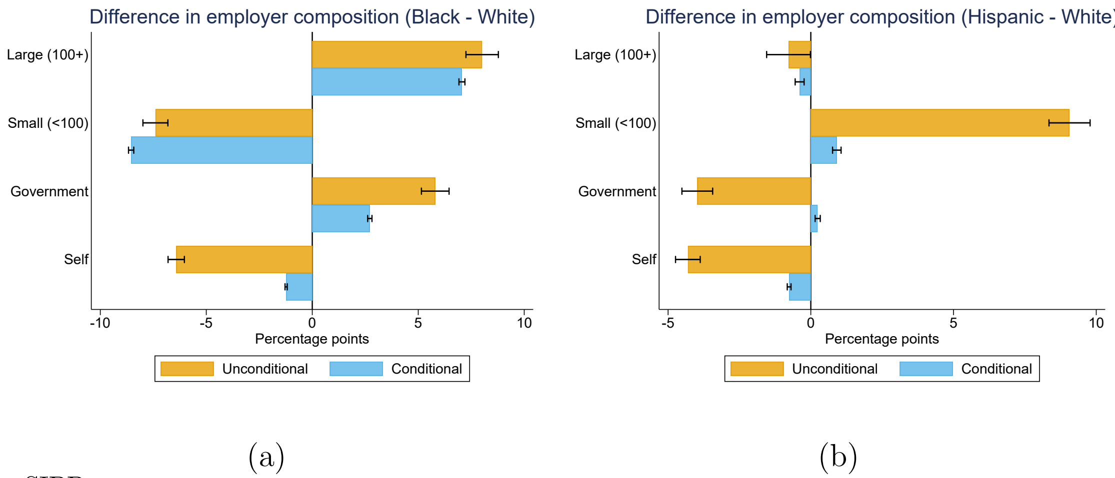


Source: ASEC supplement to the CPS
Bars represent the average annual fraction of workers who report each employer type as their primary job over the prior year. The sample covers the adult population aged 18-65 from 1988-2020.

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 A.2 reports similar patterns using the ASEC data both with large firms defined as 100 or more employees and 500 or more.

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

Figure 3: Conditional gaps in employer composition by race and ethnicity



Source: SIPP
Conditional estimates control for age and age-squared by gender, education, occupation, industry, and state.

these different patterns in 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 also makes 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 hiring and separation patterns by race and firm size contribute to the racial employment gap and its movements over the business cycle. I find that small firms contribute most to the baseline gap in employment rates, whereas large firms contribute most to the worsening of the gap with the business cycle.

3.1. Decomposition framework

Consider the evolution of the employment rate for a group of workers, assuming the population size is fixed

$$e_{gt} = (1 - e_{gt-1}) \times \lambda_{gt}^{NE} + e_{gt-1} \times (1 - \lambda_{gt}^{EN})$$

where e_{gt} is the employment to population ratio of group g at month t and λ_{gt}^{ij} is the probability that a worker moves from state i to state j. Thus λ_{gt}^{NE} is the inflow rate from nonemployment to employment and λ_{gt}^{EN} is the outflow rate from employment to nonemployment.

Suppose there are J types of employers in the economy indexed by j. The total inflow rate can be defined as the sum of the probabilities that a nonemployed worker moves from nonemployment into each of the J types of jobs,

$$\lambda_{gt}^{NE} = \sum_j \lambda_{gt}^{Nj}$$

The total outflow rate is defined as the weighted average of outflow rates from each type of employer, using each employer's share of total employment in the previous month as the weight,

$$\lambda_{gt}^{EN} = \sum_j \frac{e_{gjt-1}}{e_{gt-1}} \lambda_{gt}^{jN}$$

Using these expressions, the evolution of employment for group g can be expressed as the following

$$e_{gt} = (1 - e_{gt-1}) \sum_j \lambda_{gt}^{Nj} + \sum_j e_{gjt-1}(1 - \lambda_{gt}^{jN}) \tag{1}$$

where e_{gjt} is employment at type j firms as a share of total population, and λ^{ij} is the transition rate from state i to state j. For example, λ^{NL} is the transition rate from nonemployment

(N) to employment at a large firm (L).

Now, we can use this framework to evaluate the employment gap, $\Delta_g e_{gt}$, where the Δ_g operator is defined as the difference over $g_1 - g_0$. Manipulating equation (1) and differencing across groups, the employment gap can be written as

$$\begin{aligned}\Delta_g e_{gt} = &\underbrace{\Delta_g e_{gt-1}\left((1-\lambda^{EN}_{g_0 t}) - \lambda^{NE}_{g_0 t}\right)}_{\text{persistence}} + \underbrace{e_{g_1 t-1}\sum_j \left((1-\lambda^{jN}_{g_0 t}) - \lambda^{NE}_{g_0 t}\right)\Delta_g \frac{e_{gjt-1}}{e_{gt-1}}}_{\text{composition}} \\ &+ \sum_j \underbrace{(1-e_{g_1 t-1})\Delta_g \lambda^{Nj}_{gt}}_{\text{hiring } j} - \sum_j \underbrace{e_{g_1 jt-1}\Delta_g \lambda^{jN}_{gt}}_{\text{separation } j} \end{aligned} \tag{2}$$

The first term can be interpreted as the persistence of the employment gap from the previous month, or the evolution of the employment gap if there were no differences in hiring or separation rates or composition across employers. If turnover is higher, the persistence term will be lower in absolute terms. The second term is the contribution of differences in employer composition, essentially reweighting the total persistence to account for differences in exposure to employer type-specific separation rates. If group 1 is more likely to work for firms with higher separation rates, then this will contribute negatively to the employment gap. The third and fourth terms represent the contributions of differences in hiring and separation rates by group and firm size. If group 1 faces a lower hiring rate or a higher separation rate, this will also contribute negatively to the employment gap.

Next, consider a shock that affects macroeconomic conditions, ε_t. We can evaluate the channels through which this shock affects the employment gap by differentiating each term in Equation (2), giving the following expression

$$\begin{aligned}\frac{\partial \Delta_g e_{gt}}{\partial \varepsilon_t} = &-\underbrace{\Delta_g e_{gt-1}\left(\frac{\partial \lambda^{EN}_{g_0 t}}{\partial \varepsilon_t} + \frac{\partial \lambda^{NE}_{g_0 t}}{\partial \varepsilon_t}\right)}_{\text{persistence}} - \underbrace{e_{g_1 t-1}\sum_j \left(\frac{\partial \lambda^{jN}_{g_0 t}}{\partial \varepsilon_t} + \frac{\partial \lambda^{NE}_{g_0 t}}{\partial \varepsilon_t}\right)\Delta_g \frac{e_{gjt-1}}{e_{gt-1}}}_{\text{composition}} \\ &+ \sum_j \underbrace{(1-e_{g_1 t-1})\Delta_g \frac{\partial \lambda^{Nj}_{gt}}{\partial \varepsilon_t}}_{\text{hiring } j} - \sum_j \underbrace{e_{g_1 jt-1}\Delta_g \frac{\partial \lambda^{jN}_{gt}}{\partial \varepsilon_t}}_{\text{separation } j} \end{aligned} \tag{3}$$

Given a negative employment gap in the previous month, the persistence term will be negative if the hiring rate (λ^{NE}) decreases by more than the separation rate (λ^{EN}) increases. The composition term will be more negative if group 1 has a higher employment share at firms that increase separations by more. The hiring and separation terms will be negative if group 1 is less likely to be hired and more likely to be fired.

The level decomposition (2) can be evaluated with mean employment and transition rates from the SIPP. For the business cycle decomposition (3), I need a framework for evaluating how these transition rates respond to macroeconomic conditions.

3.2. Transition rates over the business cycle

As a baseline, I estimate the gap in cyclical hiring rates using a linear regression framework,

$$\mathbb{P}\left[E_{it}^{j}=1|N_{it-1}=1\right]=\alpha_{Nj}+\alpha_{Nj}^{B}\text{Black}_i+\Gamma_{Nj}X_{it}+\beta_{Nj}\text{UR}_t+\beta_{Nj}^{B}\text{Black}_i\times\text{UR}_t+u_{it} \quad (4)$$

where the outcome variable is an indicator equal to 1 if person i is employed by a type j firm in month t and 0 otherwise, including only the sample of individuals who were nonemployed in the previous month. Black_i is a racial dummy variable and UR_t is a macroeconomic variable. As a baseline, I use the headline unemployment rate but I also use log vacancies and GDP in deviations from trend. X_{it} is a vector of individual characteristics, including age, age-squared, gender, education, state, urban/rural, modal occupation/industry. I cluster standard errors by individual. I use the same structure for separation rates, $\mathbb{P}\left[N_{it}|E_{it-1}^{j}\right]$.

The linear framework has the advantage that the coefficients of interest directly map to the hiring or separation gap in Equations (2) and (3), with some additional scaling. In particular, $\Delta_g\lambda_{gt}^{Nj}$ in Equation (2) maps to $(\alpha_{Nj}^{B}+\Gamma_{Nj}(\bar{X}_{it}^{B}-\bar{X}_{it}^{W}))$. In the cycle decomposition, β_{Nj}^{B} maps to $\Delta_g(\partial\lambda_{gt}^{Nj}/\partial\varepsilon_t)$ in Equation (3). It is also comparable to the linear framework used by other studies without the firm size distinction, notably Couch & Fairlie (2010). The disadvantage is that estimating each of these separately does not account for the other possible outcomes, i.e. hiring at small firms being affected by hiring at large firms. To more flexibly account for the full system of transitions, I estimate a multinomial logit model in Section 3.4.

Table 1: Cyclical job finding rates

	(1) Total	(2) Large	(3) Small	(4) Government	(5) Self
Black (α^B)	-0.5768***	-0.0312	-0.4399***	-0.0290**	-0.0646***
	(0.0445)	(0.0299)	(0.0229)	(0.0128)	(0.0073)
UR (β)	-0.2176***	-0.0942***	-0.0800***	-0.0174***	-0.0130***
	(0.0081)	(0.0049)	(0.0045)	(0.0025)	(0.0014)
Black × UR (β^B)	-0.0554**	-0.0606***	0.0086	-0.0109*	0.0081**
	(0.0224)	(0.0149)	(0.0112)	(0.0064)	(0.0035)
N	2,542,427	2,542,427	2,542,427	2,542,427	2,542,427
Outcome mean (White)	2.320	1.003	0.853	0.251	0.123
Outcome mean (Black)	2.541	1.386	0.716	0.260	0.090

Standard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Results from estimating Equation (4) for the probability of moving from nonemployment to employment at each type of firm. The units are percentage points. UR is the headline unemployment rate in percentage points, with mean 0 and standard deviation 1.8. Controls are included for age, age-squared, gender, education, state, urban/rural, and modal occupation/industry. Standard errors are clustered at the individual level. The sample includes all non-Hispanic Black and white individuals age 20 and older who were not employed in the previous month.

Table (1) shows the results for job-finding probabilities. Starting with the first column, after controlling for differences in observable characteristics, Black workers are 58 basis points less likely to move from nonemployment to employment. When the overall unemployment rate is one percentage point higher, all workers are 22 basis points less likely to move into employment, but Black workers face an additional 5.5 basis point drop in the job-finding rate. Moving across the columns, the remaining coefficients in each row should sum to the coefficient in the first column.[3] From the first row, we can see that the baseline hiring gap is coming from the small firms. Next, for white workers the total 22 basis point drop in hiring is roughly evenly distributed between large and small firms. Finally, the cyclical gap in hiring rates is driven by large firms.

Table (2) reports the results for the separation rates. From the first column, Black workers are conditionally 16 basis points more likely to separate from employment to nonem-

[3] They would sum exactly if I exclude workers whose employer type is missing from the sample.

Table 2: Cyclical separation rates

	(1) Total	(2) Large	(3) Small	(4) Government	(5) Self
Black (α^B)	0.1553***	0.2502***	0.3018***	-0.1270***	0.2034***
	(0.0262)	(0.0363)	(0.0649)	(0.0402)	(0.0585)
UR (β)	0.0095**	0.0137**	0.0203**	0.0093	-0.0018
	(0.0045)	(0.0065)	(0.0103)	(0.0091)	(0.0066)
Black × UR (β^B)	-0.0286**	-0.0420**	-0.0643*	0.0117	0.0480
	(0.0141)	(0.0194)	(0.0355)	(0.0217)	(0.0329)
N	4,118,950	1,857,269	1,046,868	687,843	482,692
Outcome mean (White)	1.282	1.265	1.767	0.955	0.464
Outcome mean (Black)	1.558	1.666	2.106	0.810	0.776

Standard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Results from estimating Equation (4) for the probability of moving from employment at each type of firm to nonemployment. The units are percentage points. UR is the headline unemployment rate in percentage points, with mean 0 and standard deviation 1.8. Controls are included for age, age-squared, gender, education, state, urban/rural, and modal occupation/industry. Standard errors are clustered at the individual level. The sample includes all non-Hispanic Black and white individuals age 20 and older who were not employed in the previous month.

ployment. When the unemployment rate increases by one percentage point, the separation rate for white workers increases by one basis point. Meanwhile, the separation gap between Black and white workers attenuates by 3 basis points. This negative interaction term is in contrast to the "first fired" literature, though it is consistent with more recent research showing that fluctuations in hiring are more important for the cyclical employment gap between non-white and white workers (Forsythe & Wu (2021)). This difference could be coming from my focus on nonemployment rather than unemployment and also using a wider sample. Couch & Fairlie (2010) focus on men aged 25-55 in their study and find that the separation rate increases more for Black men in response to increases in the unemployment rate. If I limit my sample to this same group and focus on unemployment, I also find a weakly positive coefficient for the interaction term. However, to the extent that policymakers care about a broader population when assessing the implications of business cycle fluctuations, this restriction is very limiting.

3.3. Decomposition results

Equipped with these estimates of transition rate gaps and their responsiveness to business cycle conditions, I can construct the decompositions of the employment gap in levels and in response to movements in aggregate conditions, as proxied by the unemployment rate. I use the fitted values from Equation (4) as my estimates for λ^{ij}_{gt}. Table (3) reports the estimates for the decomposition reported in Equation (2) with Black workers as group 1 and white as group 0. First, the employment gap is highly persistent. The vast majority of the average employment gap over the sample period is explained by the employment gap in the previous month. The composition of employers makes a negligible positive contribution to the gap. Small firms tend to have higher average turnover, which means sorting more towards large firms should favor the Black employment rate relative to white. Next, I break up the differences in transition rates into the portion explained by observable characteristics, like education, industry, etc., and the residual term, α^B_{ij} in Equation (4). Observable characteristics make Black workers more likely to be hired and somewhat more likely to separate, leading to a positive contribution of net turnover. For the residual terms, however, Black workers are both less likely to be hired and more likely to separate, leading to an overall negative effect on the employment gap. Looking at the source of this unexplained gap, the largest negative contribution is coming from lower hiring at small firms.

Table 3: Decomposition: Average employment gap

	Persistence	Composition	Hiring		Separation	
			Explained	Residual	Explained	Residual
	-4.10	**0.004**	**0.32**	**-0.23**	**-0.06**	**-0.11**
Large			0.166	-0.013	-0.047	-0.078
Small			0.122	-0.177	-0.004	-0.036
Government			0.015	-0.012	0.002	-0.007
Self			0.013	-0.026	-0.004	-0.007

Decomposition terms are defined in Equation (2), where the gap is measured as Black - white. Transition rates λ^{ij} are constructed using fitted averages from the estimates from Equation (4). The residual term corresponds to the α_{ij} coefficient from Equation (4).

Table (4) reports the estimates for the change in the employment gap in response to macroeconomic conditions, defined in Equation (3). In this case, the differential hiring response by large firms makes the largest negative contribution to the change in the employment gap, though it is partially offset by the positive contribution of differential separations. Small firm responses, meanwhile, make positive contributions. Thus, although small firms are the most important for explaining the baseline racial employment gap, large firms are more important for understanding its movements over the business cycle.

Table 4: Decomposition: Change in employment gap

	Persistence	Composition	Hiring	Separation
Large			-0.0244	0.0131
Small			0.0035	0.0077
Government			-0.0044	-0.0015
Self			0.0033	-0.0017
	-0.0089	**-0.0008**	**-0.0223**	**0.0191**

Decomposition terms are defined in Equation (3), where the gap is measured as Black - white. Transition rates λ^{ij} are constructed using fitted averages from the estimates from Equation (4). The responses to macroeconomic shocks $\frac{\partial \lambda^{ij}}{\partial \varepsilon}$ and $\Delta_g \frac{\partial \lambda^{ij}}{\partial \varepsilon}$ correspond to coefficients β_{ij} and β^B_{ij}, respectively.

3.4. Multinomial logit

To provide a more complete picture of the full transition matrix across employer types by race and how it varies over the business cycle, I use a multinomial logit framework to estimate the probability of a worker moving from state j to state k. For example, the relative probability of moving from nonemployment to employment at a type j firm is

$$\frac{\mathbb{P}\left[E^j_{it} = 1 | N_{it-1} = 1\right]}{\mathbb{P}\left[N_{it} = 1 | N_{it-1} = 1\right]} = \exp(\alpha_{Nj} + \alpha^B_{Nj}\text{Black}_i + \Gamma_{Nj} X_{it} + \beta_{Nj}\text{UR}_t + \beta^B_{Nj}\text{Black}_i \times \text{UR}_t + u_{it}) \tag{5}$$

Table (10) in Appendix B reports the results for each of the five starting employment states. Similar to the linear framework, Black workers are less likely to move from nonemployment to small firms, and also less likely to move from other employment states to small firms at baseline. Over the cycle, the interaction term on the Black dummy and unemployment rate for the transition from nonemployment to large firm employment is still negative and statistically significant. The separation rate interaction terms are still negative for large and small firms, though not statistically significant.

4. Model

I develop a quantitative model to evaluate how differences in workers' access to referral networks across firm sizes contribute to the effects observed in the data by race and firm size. The model features heterogeneous firms, heterogeneous workers, and a frictional labor market.

4.1. Environment

The model is set in discrete time.

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

$$x = p(g, z)s + (1 - p(g, z))\mathbb{E}[s] \tag{6}$$

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

$$J_t(n_B, n_W, z) = \max_{v \geq 0, x_g} -c_v(z)v + a_t z(n')^\alpha \tag{7}$$

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

s.t.

$$n' = \sum_g n'_g \tag{8}$$

$$n'_g = (1-\delta_t)n_g + \hat{x}(x_g, p(g, z))h_g \tag{9}$$

$$h_g = \frac{u_{gt}}{u_t} q(\theta_t) v(1 - F(x_g | p(g, z))) \tag{10}$$

$$\bar{x}(p(g, z)) - p(g, z) \leq x_g \leq \bar{x}(p(g, z)) \tag{11}$$

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, $F(\cdot)$.

$$\bar{x}(p) = p + (1-p)\mathbb{E}[x] \tag{12}$$

$\bar{x}(p)$ 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.

$$F(x|p) = F\left(\frac{x - (1-p)\mathbb{E}[x]}{p}\right) \tag{13}$$

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

$$\hat{x}(x,p) = \frac{\int_x^{\bar{x}(p)} y dF(y|p)}{1 - F(x|p)} \tag{14}$$

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

$$q(\theta_t)v = \frac{h_B}{\frac{u_{Bt}}{u_t}(1 - F(x_B|p(B,z)))} = \frac{h_W}{\frac{u_{Wt}}{u_t}(1 - F(x_W|p(W,z)))} \tag{15}$$

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,

$$V_t^n(g,z) = w_t^n(n', z, g) + \beta\mathbb{E}_t\left[V_{t+1}^u(g) + (1-\delta)(V_{t+1}^n(g,z) - V_{t+1}^u(g))\right] \tag{16}$$

Newly hired workers can be paid different wages and face higher separation rates, captured in the value function $V_t^h(g,z)$[4]

$$V_t^h(g,z) = w_t^h(x_g(z), n', z, g) + \beta\mathbb{E}_t\left[V_{t+1}^u(g) + \hat{x}(x_g(z), p(g,z))(1-\delta)(V_{t+1}^n(g,z) - V_{t+1}^u(g))\right] \tag{17}$$

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

$$\begin{aligned} V_t^u(g) &= b + \beta\mathbb{E}_t V_{t+1}^u(g) \\ &\quad + \underbrace{\beta\mathbb{E}_t\left[\theta_{t+1}q(\theta_{t+1})\sum_z \frac{\mu(z)v^(z)}{V}(1 - F(x_g(z)|p(g,z)))(V_{t+1}^h(g,z) - V_{t+1}^u(g))\right]}_{\Omega_t(g)} \end{aligned} \tag{18}$$

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.

[4]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,

$$\begin{aligned} D_t(\{\tilde{n}_g\}, \{h_g\}, \{x_g\}, z) =& a_t z (n')^\alpha - \sum_g \left(\tilde{n}_g w^n(n', z, g) + h_g w^h(x_g, n', z, g)\right) \\ &+ \beta \mathbb{E}_t J_{t+1}(n'_B, n'_W, z) \\ &\text{s.t.} \\ &n'_g = \tilde{n}_g + \hat{x}(x_g, p(g,z)) h_g \end{aligned} \tag{19}$$

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 (10), and $\hat{x}(x_g(z), p(g,z))$ is the expected productivity of new hires as defined in Equation (14).

Firms and workers split the surplus according to the following rules

$$\phi D_{t,\tilde{n}_g} = (1-\phi)\left(V_t^n(g,z) - V_t^u(g)\right) \tag{20}$$

$$\phi D_{t,h_g} = (1-\phi)\left(V_t^h(g,z) - V_t^u(g)\right) \tag{21}$$

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,

$$w^n(n', z, g) = \frac{\alpha\phi}{1-\phi+\alpha\phi} a_t z n'^{\alpha-1} + (1-\phi)(b + \Omega_t(g)) \tag{22}$$

$$w^h(x_g, n', z, g) = \hat{x}(x_g, p(g,z)) \frac{\alpha\phi}{1-\phi+\alpha\phi} a_t z n'^{\alpha-1} + (1-\phi)(b + \Omega_t(g)) \tag{23}$$

where $\Omega_t(g)$ is the value of searching next period for a worker from group g as defined in Equation (18). 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

$$u_{gt+1} = 1 - \frac{1}{\pi(g)} \sum_z \mu(z) \left(n'_g(z) + h_g(z)(1 - \hat{x}(x_g(z), p(g,z))) \right) \tag{24}$$

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

$$\Gamma(z) = \frac{\mu(z) \sum_g ((1-\delta)n_g(z) + h_g(z))}{\sum_{\tilde{z}} \mu(\tilde{z}) \sum_g ((1-\delta)n_g(\tilde{z}) + h_g(\tilde{z}))} \tag{25}$$

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

$$
\begin{aligned}
C_t(\Delta_B, \Delta_W) = \min_{\{x_g\}} & \sum_g \frac{\Delta_g}{\hat{x}(x_g, p(g,z))} \left(\frac{c_v(z)}{q(\theta_t)(1 - F(x_g | p(g,z)))} + (1-\phi)(b + \Omega_t(g)) \right) \\
& \text{s.t. } (15)
\end{aligned} \tag{26}
$$

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,

$$
\begin{aligned}
\frac{\partial C_t(\Delta_B, \Delta_W)}{\partial \Delta_g} & + \beta(1-\delta)\mathbb{E}_t \left[(1-\phi)(b + \Omega_{t+1}(g)) \right] \\
& = \frac{\alpha(1-\phi)}{1-\phi+\alpha\phi} a_t z (n')^{\alpha-1} + \beta(1-\delta)\mathbb{E}_t \left[\frac{\partial C_{t+1}(\Delta'_B, \Delta'_W)}{\partial \Delta'_g} \right]
\end{aligned} \tag{27}
$$

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

$$\frac{\partial C_t(\Delta_B, \Delta_W)}{\partial \Delta_g} = \frac{(1-\phi)(b+\Omega_t(g))}{x_g} \tag{28}$$

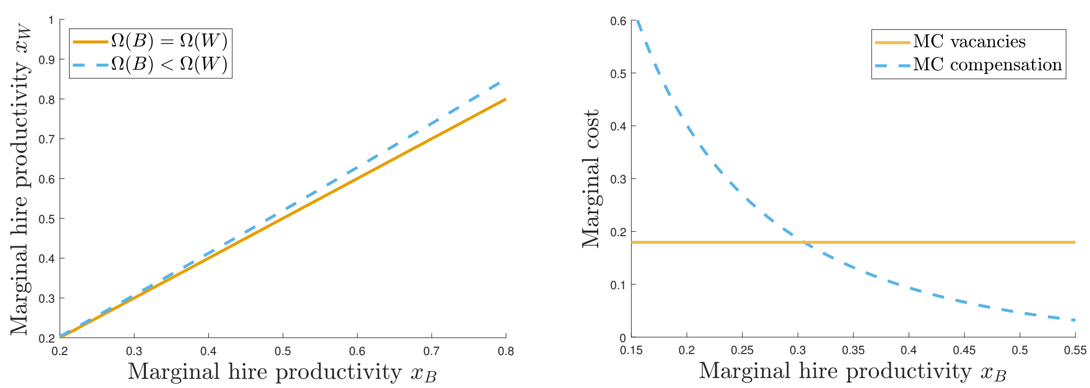
which can be interpreted as the compensation cost for the marginal hire, as the firm needs to hire $\frac{1}{x_g}$ workers to hire the last productive worker.

Equations (27) and (28) can be combined to show the relationship between the hiring thresholds for the two groups.

$$\begin{aligned} 0 =& \frac{(b+\Omega_t(B))}{x_B} - \beta(1-\delta)\mathbb{E}_t\left[(b+\Omega_{t+1}(B))\frac{1-x_B'}{x_B'}\right] \\ &- \frac{(b+\Omega_t(W))}{x_W} + \beta(1-\delta)\mathbb{E}_t\left[(b+\Omega_{t+1}(W))\frac{1-x_W'}{x_W'}\right] \end{aligned} \tag{29}$$

Panel (a) of Figure 4 shows this relationship in steady state where $\Omega_t(g) = \mathbb{E}[\Omega_{t+1}(g)] = \Omega(g)$. 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

Figure 4: Marginal hire productivity between groups



(a) (b)

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

$$\frac{c_v(z)}{q(\theta_t)} = \sum_g \frac{u_{gt}}{u_t}(1-\phi)(b+\Omega_t(g))\frac{(\hat{x}(x_g, p(g,z)) - x_g)}{x_g}(1 - F(x_g|p(g,z))) \tag{30}$$

The left side of Equation (30) is the marginal vacancy cost, which is constant due to the linear vacancy technology. The right side of Equation (30) 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 Elsby & Michaels (2013)

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

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 0.118 based on the share of Black relative to white population in the SIPP.

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 5: 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	0.118	SIPP
ζ	Matching scale	.283	Avg. hired share 0.1
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 small 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 here and leave formal details to Appendix C. 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.

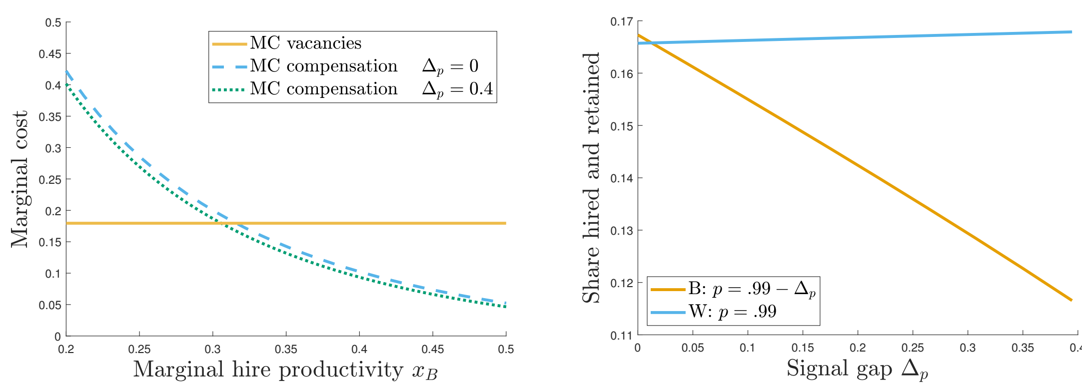
The final estimated parameters are the signal gaps at large and small firms. These are identified by the minority share of employment at each type of firm. Consider the partial equilibrium effects of increasing the signal quality gap between majority and minority workers for the firm's optimal threshold solution in equation (30). 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 6: Fitted Parameters

Parameter	Meaning	Baseline
Scale parameters		
μ	Number firms/worker	0.007
b	Flow value unemp	0.997
ϕ	Bargaining power	0.272
γ	Match quality shape	4.53
Estimated parameters		
δ	Exog. separation	0.011
$c_v(L)$	Vacancy cost	0.001
$c_v(S)$	Vacancy cost	0.062
$\frac{z(L)}{z(S)}$	Relative productivity	4.142
$\Delta_p(L)$	Signal gap, large	0.079
$\Delta_p(S)$	Signal gap, small	0.395

signal above the chosen threshold, and the average productivity conditional on being above that threshold also decreases.[5] 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 7: Moments, percentage points

(a) *Targeted*

Moment	Data/Model
Separation rate	1.49
Employment share	
Large	64.43
Job-finding rate	
Large	1.08
Small	0.90
Minority share	
Large	12.06
Small	9.25
Hired share matches*	
Large	5.02

(b) *Untargeted*

Moment	Data	Model
Separation rate		
Large	1.30	1.26
Small	1.82	1.90
Job-finding gap (B-W)		
Large	-0.13	-0.002
Small	-0.58	-0.10
Separation gap (B-W)		
Large	0.25	0.08
Small	0.30	0.51
Hired share matches*		
Small	10.04	27.60

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 7. Panel (b) shows the fit for untargeted moments. I match the average separation rate by construction, but the model matches the distribution across firm size reasonably well. 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 fit in terms of hiring and separation gaps is likely off because 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).

[5]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. Business cycle dynamics

6.1. Comparative steady states

As a first exercise, I use the quantitative model to consider a permanent negative shock to aggregate productivity, a. I choose the scale of the decrease such that the total drop in job finding for white workers matches the empirical results in Table 1. Because I only have small and large employers in my model, I construct the data comparisons for the model by summing columns (2) and (3).

Table 8 reports the results of this exercise. 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 8: Steady state comparison

Changes: low - high productivity		
	Data	**Model**
White job finding rate ($\beta_{NL} + \beta_{NS}$)	-0.174	-0.174
Large (β_{NL})	-0.094	-0.091
Small (β_{NS})	-0.080	-0.083
Job finding gap ($\beta^B_{NL} + \beta^B_{NS}$)	-0.052	-0.035
Large (β^B_{NL})	-0.061	-0.029
Small (β^B_{NS})	0.009	-0.006

This table shows the comparison between a low productivity steady state relative to baseline. The units are percentage points. The decrease in productivity is 0.013 log points, chosen such that 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 (2) and (3) of Table 1, which show the response of the size-specific job-finding rates to an increase in the headline unemployment rate.

The second group of Table 8 shows the change in the job-finding gap. In the data the job-finding gap drops by 5.2 basis points and the model captures 3.5 basis points of that drop. Looking at the split between large and small firms, the model also captures that this drop is strongest for large firms. Using the model, we can decompose why the drop is larger

Table 9: Job-finding gap components

	Total gap	Matching rate	Vacancy share	Relative selectivity
Large firm				
High a	-0.002	0.248	0.868	-0.009
Low a	-0.031	0.235	0.870	-0.15
Small firm				
High a	-0.100	0.248	0.132	-3.05
Low a	-0.106	0.235	0.130	-3.44

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 31. The first two are expressed as fractions and the last is in percentage points.

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

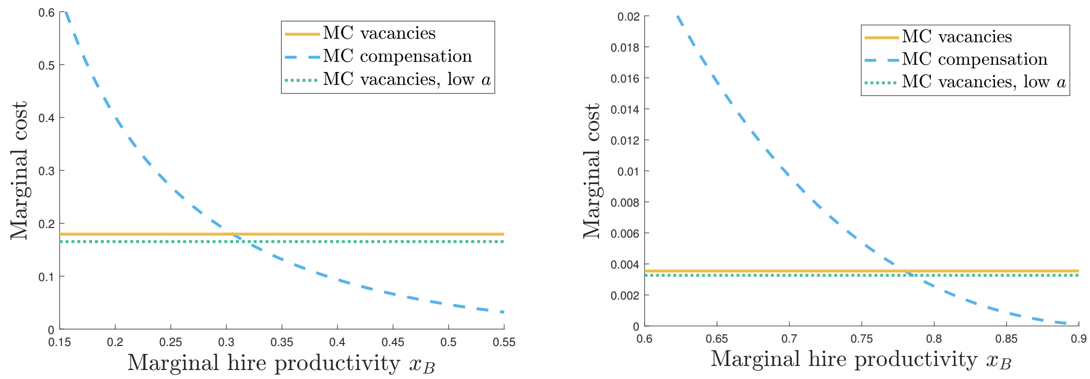
$$\underbrace{\theta q(\theta)}_{\text{matching rate}} \underbrace{\frac{\nu(z)v(z)}{\sum \nu(z)v(z)}}_{\text{vacancy share}} \underbrace{\Big((1 - F(x_B|p(B,z))) - (1 - F(x_W|p(W,z)))\Big)}_{\text{relative selectivity}} \tag{31}$$

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 9 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 baseline (high a) 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 baseline steady state, large firms hired 0.009 ppt fewer Black matches than white, whereas small firms hired 3.05 ppt fewer. In the low productivity state, this gap widens by 0.06 ppt at large firms and 0.39 ppt at small firms.

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 (30). When market tightness is lower, firms match with more workers per vacancy, shifting the marginal

Figure 6: Change in selectivity with aggregate productivity



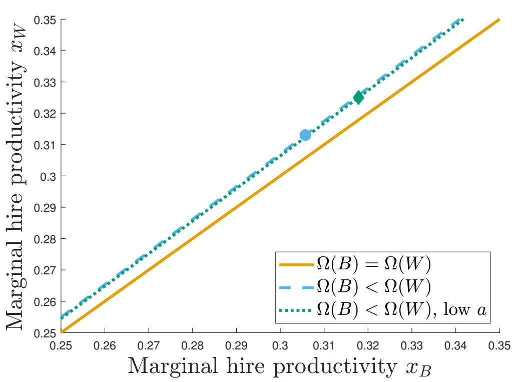
(a) Small firm (b) Large firm

This figure shows the tradeoff in the firm's decision between vacancy posting and selectivity, defined in Equation (30). Panel (a) shows the problem for the small firm, which faces a higher marginal vacancy cost and a noisier signal about minority worker productivity. Panel (b) shows the same for the large firm. The orange (solid) line is the marginal cost of vacancies, $c_v(z)/q(\theta)$. In the low productivity state, $q(\theta)$ increases and this curve shifts down to the green (dotted) line. Both firms increase selectivity by choosing a higher marginal productivity threshold, at the new intersections with the blue (dashed) marginal cost of compensation.

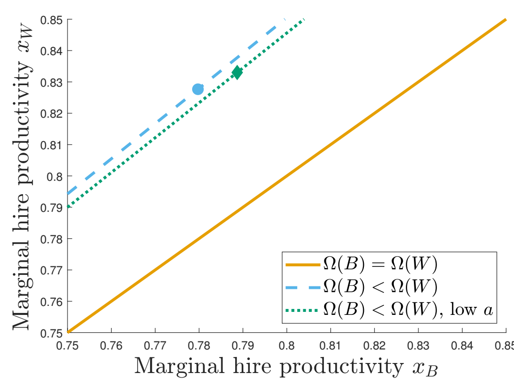
vacancy cost curve down. This partial equilibrium effect is illustrated in Figure 6. It is now cheaper for firms to be selective about which workers they hire, shown by the new intersections at higher marginal productivity of minority workers for both firms. In general equilibrium, there are also effects on the marginal compensation cost as the workers' outside options adjust and the minority share of nonemployment rises that affect the marginal cost of compensation. However, these effects are quantitatively small and the blue (dashed) line in Figure 6 is indistinguishable when plotted with the shifted marginal compensation cost curve.

The disproportionate effect of this increase in selectivity on minority workers comes from two sources. First, the distribution of beliefs about worker productivity is compressed for minority workers due to the worse signal quality. Suppose the thresholds for both groups were starting at the same point and shifted up by the same amount. Then this will have a stronger effect on minority workers because the underlying shape of the distribution is the same for both groups but the distribution of beliefs is more compressed for the workers with the noisier signal. 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. Recall from Equation (27) and Panel (a) of Figure 4 that a lower outside option for Black workers means the the firm sets a higher marginal threshold for white workers, as their compensation needs to be higher. Figure 7 shows that with the lower negative aggregate productivity, the compensation gap narrows and thus the relationship between thresholds shifts slightly closer to the 45-degree line. This change is barely perceptible at the point of the curve that the small firm is locating. In Panel (a), the blue (dashed) line is the original relationship between marginal productivities and the green (dotted) line is the relationship in the low productivity state. The blue dot represents the original threshold and the green diamond is the threshold in the low productivity state. At the part of the curve where the large firm is locating, however, the difference between these curves is more perceptible. Panel (b) shows that as the firm increases its threshold from the blue dot to the green diamond, it also shifts to the lower frontier between thresholds. This means that it increases selectivity by less for white workers than it would have in the original state. This serves to worsen the change in the hiring gap more at large firms.

Figure 7: Change in selectivity with aggregate productivity



(a) Small firm



(b) Large firm

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. The direct effect of this is bigger at small firms because they have the wider gap in signal quality and higher vacancy cost. However, the indirect effect is bigger at large firms through general equilibrium effects on compensation. The total observed change in the job-finding gap is worse at large firms mainly because they make up a larger share of the market.

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 hiring 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.

In future work, it will be worth exploring how these patterns vary within firm-size classes. Given the limitations of the SIPP and other publicly-available data, I have representative small and large firms in this paper, but linked employer-employee data would provide more nuance. In particular, Ferguson & Koning (2018) show that racial establishment segregation has increased over the last few decades. This would imply that differences in networks could be leading to changes in application behavior. The effects that this has on the outlook for the distributional effects of future recessions is worth studying.

References

Aaronson, Stephanie R., Wascher, William L., Daly, Mary C., & Wilcox, David W. 2019. Okun revisited: Who benefits most from a strong economy? *Brookings Papers on Economic Activity*, **2019**(Spring), 333–404.

Axtell, Robert L. 2001. Zipf Distribution of U.S. Firm Sizes. *Science*, **293**(5536), 1818–1820.

Barron, John M., Berger, Mark C., & Black, Dan A. 1997. Employer Search, Training, and Vacancy Duration. *Economic Inquiry*, **XXXV**, 167–192.

Bartscher, Alina K., Kuhn, Moritz, Schularick, Moritz, & Wachtel, Paul. 2021. Monetary Policy and Racial Inequality. *Federal Reserve Bank of New York Staff Reports*.

Baydur, Ismail. 2017. Worker Selection, Hiring, and Vacancies. *American Economic Journal: Macroeconomics*, **9**(1), 88–127.

Bergman, Nittai, Matsa, David A., & Weber, Michael. 2020. Heterogeneous Labor Market Effects of Monetary Policy.

Black, Dan A. 1995. Discrimination in an Equilibrium Search Model. *Journal of Labor Economics*, **13**(2), 309–334.

Cajner, Tomaz, Radler, Tyler, Ratner, David, & Vidangos, Ivan. 2017. Racial Gaps in Labor Market Outcomes in the Last Four Decades and over the Business Cycle. *Finance and Economics Discussion Series*, **2017-071**.

Carpenter, Seth B., & Rodgers III, William M. 2004. The disparate labor market impacts of monetary policy. *Journal of Policy Analysis and Management*, **23**(4), 813–830.

Couch, Kenneth A, & Fairlie, Robert. 2010. Last Hired, First Fired? Black-White Unemployment and the Business Cycle. *Demography*, **47**(1), 227–247.

Elsby, Michael W. L, & Michaels, Ryan. 2013. Marginal Jobs, Heterogeneous Firms, and Unemployment Flows. *American Economic Journal: Macroeconomics*, **5**(1), 1–48.

Ferguson, John-Paul, & Koning, Rembrand. 2018. Firm Turnover and the Return of Racial Establishment Segregation. *American Sociological Review*, **83**(3), 445–474.

Forsythe, Eliza, & Wu, Jhih-Chian. 2021. Explaining Demographic Heterogeneity in Cyclical Unemployment. *Labour Economics*, **69**, 101955.

Fujita, Shigeru, Nekarda, Christopher J, & Ramey, Garey. 2007. The Cyclicality of Worker Flows: New Evidence from the SIPP.

Haltiwanger, John C., Hyatt, Henry R., Kahn, Lisa B., & McEntarfer, Erika. 2018. Cyclical Job Ladders by Firm Size and Firm Wage. *American Economic Journal: Macroeconomics*, **10**(2), 52–85.

Holzer, Harry J. 1998. Why Do Small Establishments Hire Fewer Blacks Than Large Ones? *The Journal of Human Resources*, **33**(4), 896–914.

Hoynes, Hilary, Miller, Douglas L., & Schaller, Jessamyn. 2012 (jun). Who suffers during recessions? *Pages 27–48 of: Journal of Economic Perspectives*, vol. 26.

Jarosch, Gregor, & Pilossoph, Laura. 2019. Statistical discrimination and duration dependence in the job finding rate. *Review of Economic Studies*, **86**(4), 1631–1665.

Kuhn, Florian, & Chancí, Luis. 2021. Effects of Hiring Discrimination over the Business Cycle.

Lang, Kevin, & Lehmann, Jee-Yeon K. 2012. Racial Discrimination in the Labor Market: Theory and Empirics. *Journal of Economic Literature*, **50**(4), 959–1006.

Lee, Munseob, Macaluso, Claudia, & Schwartzman, Felipe. 2022. Minority Unemployment , Inflation , and Monetary Policy.

Menzio, Guido, & Shi, Shouyong. 2011. Efficient Search on the Job and the Business Cycle. *Journal of Political Economy*, **119**(3), 468–510.

Miller, Conrad. 2017. The Persistent Effect of Temporary Affirmative Action. *American Economic Journal: Applied Economics*, **9**(3), 152–190.

Miller, Conrad, & Schmutte, Ian M. 2021. The Dynamics of Referral Hiring and Racial Inequality: Evidence from Brazil.

Moore, Jeffrey C. 2008. *Seam bias in the 2004 SIPP panel: Much improved, but much bias still remains.* Tech. rept.

Morgan, John, & Várdy, Felix. 2009. Diversity in the workplace. *American Economic Review*, **99**(1), 472–485.

Moscarini, Giuseppe, & Postel-Vinay, Fabien. 2012. The Contribution of Large and Small Employers to Job Creation in Times of High and Low Unemployment. *American Economic Review*, **102**(6), 2509–2539.

Okafor, Chika O. 2022. All Things Equal? Social Networks as a Mechanism for Discrimination.

Petrongolo, Barbara, & Pissarides, Christopher A. 2001. Looking into the Black Box: A Survey of the Matching Function. *Journal of Economic Literature*, **39**(2), 390–431.

Stole, Lars A., & Zwiebel, Jeffrey. 1996. Intra-firm Bargaining under Non-binding Contracts. *The Review of Economic Studies*, **63**(3), 375–410.

Thorbecke, Willem. 2001. Estimating the effects of disinflationary monetary policy on minorities. *Journal of Policy Modeling*, **23**(1), 51–66.

Zavodny, Madeline, & Zha, Tao. 2000. Monetary policy and racial unemployment rates. *Economic Review- Federal Reserve Bank of Atlanta*, **85**(4), 1–59.

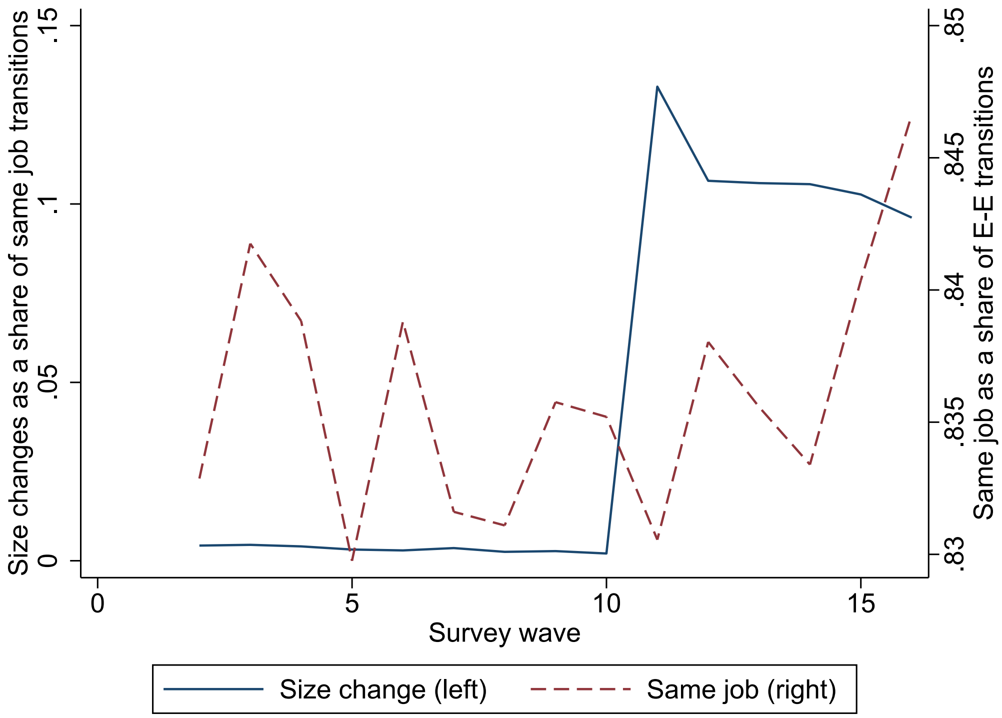
A. Additional information on background empirical facts

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.

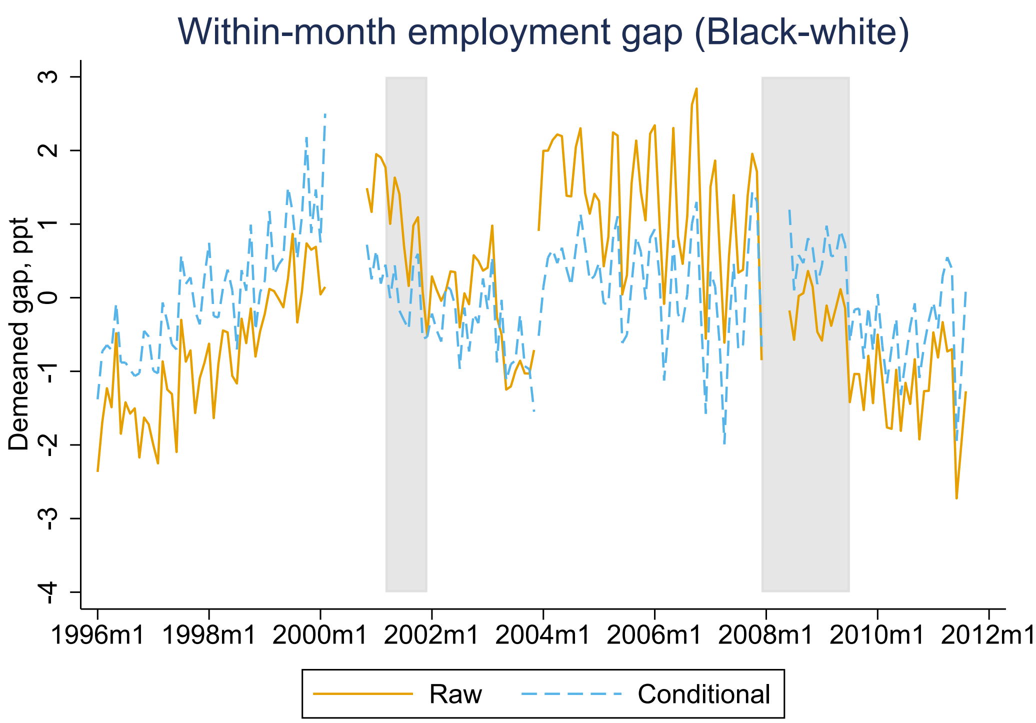


Workers are classified as having the same job if they report working for the same employer number in reference month 4 of wave $t-1$ and reference month 1 of wave t. Of those who have the same job, size changes are defined as workers who classify employer x as a small firm in wave $t-1$ and a large firm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

A.2. Additional sensitivity for background facts

Section 2.2 uses annual data from the ASEC to show that the unexplained gap in employment between Black and white workers worsens over the business cycle. This pattern is also present in the SIPP data, albeit with more noise. The correlation between the employment gap and the headline monthly unemployment rate is -0.44 for the raw measure and -0.26 for the conditional measure, both with p-values of less than 0.001. These series are not smoothed or seasonally adjusted in any way and therefore likely underestimate the correlations. Indeed, they are stronger at a quarterly or annual frequency.

Figure 9: Racial employment gap over the business cycle

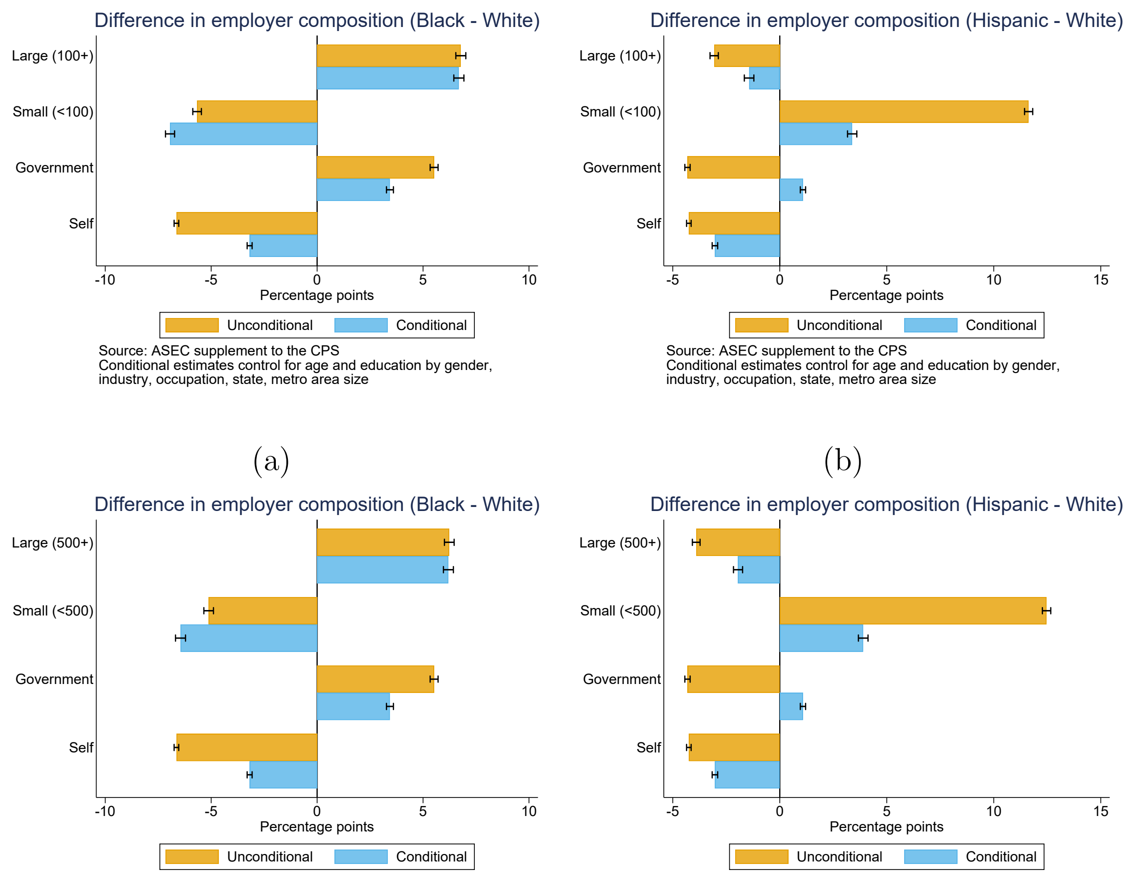


Source: SIPP.
The solid (Raw) line plots the demeaned employment gap between Black and white workers aged 20 and older. The mean is -4.2 percentage points and standard deviation 1.2. The dashed (Conditional) line plots the demeaned within-year employment gap, conditional on age and age-squared by gender, education, occupation, industry, state, and metro area size. The mean is -5.7 percentage points and standard deviation 0.7.

Figure 10 shows that the patterns over employer composition are broadly consistent between the SIPP and the ASEC and across different definitions of firm size. Panels (a) and

(b) use the same definition of large firms as Figure 3. Panels (c) and (d) report results for large firms above 500 employees.

Figure 10: Conditional gaps in employer composition by race and ethnicity



(a) (b)

(c) (d)

Source: ASEC Supplement to the CPS
Conditional estimates control for age and age-squared by gender, education, occupation, industry, state, and metro area size. Panels (a) and (b) define large firms as 100 or more employees and panels (3) and (4) use 500 employees as the threshold.

B. Additional empirical results

Table 10: Cyclical transition rates

	(1) Nonemployment$_{t-1}$	(2) Large$_{t-1}$	(3) Small$_{t-1}$	(4) Government$_{t-1}$	(5) Self$_{t-1}$
Nonemployment$_t$					
Black	0.0000	0.1962***	0.1823***	-0.1504***	0.3573***
	(.)	(0.0241)	(0.0328)	(0.0498)	(0.0872)
UR	0.0000	0.0602***	0.0594***	0.0855***	0.0713**
	(.)	(0.0119)	(0.0136)	(0.0218)	(0.0331)
Black × UR	0.0000	-0.0242	-0.0430	0.0064	0.1933**
	(.)	(0.0290)	(0.0421)	(0.0590)	(0.0975)
Large$_t$					
Black	-0.0419*	0.0000	0.1819**	0.1329	0.1636
	(0.0247)	(.)	(0.0796)	(0.1590)	(0.1518)
UR	-0.1301***	0.0000	-0.1933***	-0.1872**	-0.1104**
	(0.0121)	(.)	(0.0347)	(0.0804)	(0.0541)
Black × UR	-0.0639**	0.0000	0.1430	0.0824	-0.4476*
	(0.0288)	(.)	(0.1040)	(0.1481)	(0.2504)
Small$_t$					
Black	-0.5722***	-0.4759***	0.0000	-0.5501**	-0.3377*
	(0.0306)	(0.0815)	(.)	(0.2244)	(0.1728)
UR	-0.1055***	-0.2193***	0.0000	-0.1805**	-0.0781
	(0.0130)	(0.0384)	(.)	(0.0825)	(0.0483)
Black × UR	0.0095	0.0386	0.0000	-0.5627*	0.4871***
	(0.0362)	(0.1104)	(.)	(0.3234)	(0.1585)
Government$_t$					
Black	0.0228	0.2297*	0.3804*	0.0000	0.0747
	(0.0493)	(0.1392)	(0.2015)	(.)	(0.2850)
UR	-0.0960***	-0.2497***	-0.0798	0.0000	0.0170
	(0.0241)	(0.0728)	(0.0860)	(.)	(0.1012)
Black × UR	-0.0229	0.2878**	-0.0382	0.0000	0.6800*
	(0.0609)	(0.1435)	(0.1672)	(.)	(0.3668)
Self$_t$					
Black	-0.6212***	-0.2951*	-0.2439*	-0.3037	0.0000
	(0.0745)	(0.1515)	(0.1456)	(0.2506)	(.)
UR	-0.1480***	-0.1018*	-0.0030	-0.0928	0.0000
	(0.0291)	(0.0527)	(0.0464)	(0.1009)	(.)
Black × UR	0.1480	0.3609***	-0.1942	-0.3290	0.0000
	(0.0923)	(0.1374)	(0.1680)	(0.3458)	(.)
N	2,542,427	1,857,269	1,046,868	687,843	482,692

Standard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Results from estimating multinomial logits for the probability of moving from state i (column headers) to state j. UR is the headline unemployment rate in percentage points, with mean 0 and standard deviation 1.8. Controls are included for age, age-squared, gender, education, state, urban/rural, and modal occupation/industry. Standard errors are clustered at the individual level. The sample includes all non-Hispanic Black and white individuals age 20 and older who were not employed in the previous 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 (9).

To relate the firm value at bargaining back to the firm's problem from the main text, notice that vacancies can be rewritten as[6]

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

Then using this expression, the firm's problem from Equation (7) 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.

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

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

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

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 (20) and (21),

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

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,

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

where

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

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,

$$\begin{aligned} \sum_g \lambda_g^n \Big(V_t^n(g,z) - V_t^u(g)\Big) =& w_t^n(n',z) - \sum_g \lambda_g^n \Big((b+\Omega_t(g)) + \beta(1-\delta)\mathbb{E}_t\left[V^e_{t+1}(g,z) - V^u_{t+1}(g)\right]\Big) \\ \sum_g \lambda_g^h \Big(V_t^h(g,z) - V_t^u(g)\Big) =& w_t^h(\hat{x},n',z) \\ & - \sum_g \lambda_g^h \Big((b+\Omega_t(g)) + \beta(1-\delta)\hat{x}(x_g,p(g,z))\mathbb{E}_t\left[V^e_{t+1}(g,z) - V^u_{t+1}(g)\right]\Big) \end{aligned}$$

Using the bargaining rules defined in Equations (20) and (21),

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

and we get the following wage equations

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

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, $\Omega_t(g)$.