University of Minnesota

Essays on Racial Inequality in the Labor Market

A dissertation submitted in partial satisfaction of the requirements for the degree Doctor of Philosophy in Economics

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1 Acknowledgments

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I would especially like to thank the individuals who helped set me on the path to an economics PhD, in particular Professor Judy Dean, Murat Tasci, Ed Knotek, and Kurt Lunsford.

I would also like to thank the support staff in the Economics department at the University of Minnesota for all their assistance. Finally, I would like to express gratitude to everyone who has been there for me emotionally and intellectually as I’ve worked on my coursework and research projects.
Abstract

This dissertation studies issues related to racial inequality in the labor market. The first two chapters focus on the impact of racially segregated referral networks on inequality and aggregate welfare, while the final chapter focuses on differences in returns to work experience and the supply of labor between black and white workers in recent decades. The first chapter shows that there are racial differences in the composition of referral networks and the use of referral networks by occupation. In particular, non-college black and white workers in the United States who obtain a job via referral display substantial social segregation, using same-race contacts around 90% of the time. While non-college black and white workers use referrals at a similar rate overall, black workers use referrals for higher-skill and higher-paying occupations at a lower rate than white workers. I also document racial differences in occupational choice, with white workers sorting into higher-skill occupations. The following chapter connects and rationalize these observations by incorporating a referral-based matching function into a standard search and match model with occupational choice, heterogeneous ability levels, free entry, and wages determined by Nash bargaining. Social segregation can lead to differences in occupational choice by race, and thus wage and employment inequality, in the steady state. After calibrating the model to examine black and white workers in the United States, the estimates show that racially biased networks alone can generate a black-white wage gap of 1.66 percent and an employment gap of 0.74 percentage points. Moving from the segregated to the desegregated steady state harms the majority white workers while helping the minority black workers, resulting in a
decrease in aggregate welfare. In the final chapter I utilize individual fixed effects combined with an instrumental variables approach to document the extent to which returns to work experience differ for black and white workers; I then use a life-cycle model with a learning-by-doing human capital production function to assess the consequences of these differences for the supply of labor. Returns to an extra thousand hours of work experience for the typical white worker are 23 cents per hour in 2012 USD (amounting to an additional $478 per year of full time work), compared to 12 cents for an otherwise identical black worker (amounting to an additional $250 per year). Using a life-cycle model, differences in returns to experience combined with simulated differences in choices of hours worked can account for approximately 10 percent of the measured difference in average wages over the life-cycle between black and white workers.
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2 Chapter 1: Referral Usage by Occupation for Black and White Workers

2.1 Abstract

I first document racial differences in occupational choice, with white workers sorting into higher-skill, higher-paying occupations and black workers sorting into lower-skill, lower-paying occupations. I then delve into a potential explanation for this disparity: non-college black and white workers in the United States who obtain a job via referral display substantial social segregation, using same-race contacts around 90% of the time. This differs meaningfully by occupation, with both black and white workers relying more on white contacts for vacancy information in higher-skill, higher-paying occupations and black contacts for lower-skill, lower-paying occupations, potentially reflecting differences in who holds vacancy information for certain occupations. Beyond this, I find that non-college black and white workers use referrals at a similar rate overall. However, black workers use referrals for higher-skill and higher-paying occupations at a meaningfully lower rate than white workers.

2.2 Introduction

To what extent can racially segregated social networks perpetuate inequality? This chapter focuses on differences in access to vacancy information by race and occupation through a workers’ referral network. Previous research has established the importance of networks in the hiring process, with studies finding that approximately half of all Americans use social contacts to find jobs (Rees...
1966; Granovetter 1995; Topa 2001). These connections can provide job seekers with information about employment opportunities and improve their chances of securing a position. Studies have also shown that social networks are racially segregated, i.e. homophilous; in a national probability sample, only 8% of adults reported having a person of another race “with whom they discuss important matters” (Marsden 1987). Even if employers lack discriminatory intent, the use of referrals combined with racially structured networks of friends and families is not race-neutral. Workers’ and firms’ reliance on racially homophilous networks to facilitate matches can generate inequalities in the type of job opportunities available to black and white workers. More recent evidence on various homophilous social networks is given by Mayer and Puller (2008), Currarini et al (2009), or Zeltzer (2020). Currarini et al (2009), for example, models the friendship-formation process to examine empirical patterns in network creation.

I establish several key empirical facts. First, using the Current Population Survey (CPS) for the years 1995-2021 I show that occupational segregation for black and white non-college workers has been relatively stable for the previous two decades\(^1\). I then delve into an explanation for occupational segregation that is under-explored using the Survey of Consumer Expectations (SCE) Job Search supplement, available for 2013-2021. I show that non-college black and white workers use family/friend referrals at a similar rate to find jobs overall, but the use of referrals differ by occupation. More precisely, black workers have relatively better access to lower skill and lower paying jobs via referral networks,

\(^1\)Previous research has also documented that occupations segregated by gender, racial and ethnic groups are aligned along stable segregation paths. See Padavic and Reskin (2002), England et al (2020), and Weeden et al (2019).
while white workers have significantly better access to higher skill and higher paying jobs via referral networks. Finally, I use the Multi-City Study of Urban Inequality (MCSUI), available for the years 1992-94, to look at the rate at which workers find jobs through same-race referrals by occupation. I find substantial racial homophily; both black and white workers rely on same-race contacts approximately 90% of the time. However, the extent of this homophily differs by occupation. Both black and white workers rely more heavily on white contacts for higher skill and higher paying jobs, and black contacts for lower skill and lower paying jobs.

2.3 Literature

This paper ties together the role of referral networks in the labor market and occupational segregation. Granovetter (1973) established the foundation for network research in the social sciences. He emphasizes that employment information is intertwined with regular social interactions, and differences in the sources of information people access when finding work can affect the type of jobs they obtain. Loury (1976) is another early paper discussing racial and social inequality. While many at the time believed that eliminating overt racial discrimination would lead to the eventual elimination of racial economic inequality, Loury argues that such a view doesn’t take into account the importance of family and community background, and its effect on opportunities to acquire skills. He delves into the idea that purely a laissez-faire policy of equal opportunity is inadequate, and would perpetuate into the indefinite future historical inequalities. The results of the first two chapters of this dissertation corrob-
orate this idea, and indicate that intervention is needed to break the cycle of inequality. Since then, there have been a number of papers that focus on the relationship between social networks and inequality.

Key roles of social networks as a driver of inequality are discussed in DiMaggio and Garip (2012), Small (2009), DiMaggio and Garip (2011), and the afterward of the second edition of Granovetter (1995). DiMaggio and Garip (2012) give an overview of potential network mechanisms that can generate inequality, emphasizing that networks can exacerbate inequality when individual differences are compounded by social networks. Other papers include Braddock and McPartland (1987), who use an indirect measure (the racial composition of the respondent’s high school) to observe that Blacks who are embedded in racially segregated networks have lower incomes and are much less likely to have White coworkers than their counterparts who are embedded in racially heterogeneous networks. They conclude that racially homogenous networks disadvantage Blacks in the labor market because they contain less beneficial information about jobs, and my results complement the conclusions drawn in their research. Kugler (2003) can explain some wage inequality among equally productive workers using referrals, which is also in line with the results of my research. Beaman et al. (2018) present evidence that the use of referrals reinforces unequal access to jobs between men and women.

There are several single-firm case studies that examine race in the referral and hiring process, fining that minorities can be disadvantaged. Petersen et al. (2000) look at a mid-sized high-tech organization and find that for ethnic minorities, the hiring process is partly merit-based and partly social network
based. Once the referral method is accounted for, all race effects disappear. They conclude that ethnic minorities are disadvantaged. This study highlights the importance of referrals when it comes to racial differences in employment and hiring outcomes, although it cannot be used to examine differences across occupations. Rubineau and Fernandez (2010) analyze the segregating effects of referral networks from the perspective of individuals giving the referral. They conclude that firms can make a conscious effort to increase the volume of referrals from under-represented groups to make the recruitment process more neutral.

Occupational segregation by race is a well-studied phenomenon in the economics literature. In general, occupational segregation is thought to contribute to overall wage and employment gaps and to limit economic growth. A recent paper by Jardina, Blair, Heck and Debro y (2023) documents occupational segregation between black and white workers between 1980 and 2019, discussing how observables like educational attainment and geographic location do not account for the amount of occupational segregation that persists to this day. They discuss how desegregation has stalled in the past two decades despite gains in educational attainment by black workers. They mention the potential importance of social networks for explaining some of these trends, and here I will examine this possibility for non-college black and white workers.

2.4 Occupational Segregation

I first document an empirical pattern that confirms previous findings—that black and white workers are segregated by occupation, with black workers segregated
into less productive occupations\(^2\). I then document some novel empirical findings: the rate at which black and white individuals use social contacts is similar, but differ substantially within occupation. In particular, black workers are more likely to obtain a job through a social contact for low-paying occupations, while white workers are more likely to obtain a job through social contacts for higher-paying occupations. Further, I find that workers rely on same-race social contacts heavily regardless of occupation, but both black and white workers rely more heavily on black contacts for low skill jobs and white contacts for high skill jobs.

Occupational segregation and wage data is measured using the Current Population Survey (CPS) for the years 1995-2021, and is used to show a persistent gap in wages and occupational choice between black and white workers. IPUMS-CPS micro-data is a nationally-representative monthly sample of the US population with data starting in 1976. This analysis will focus on non-college workers, who make up the majority of the US working population and tend to rely on friend and family referrals. This is in contrast to workers holding a college degree, who tend to build up and rely on a network of business contacts\(^3\). Occupations are ranked by skill level, which is approximated by the mean real hourly wage of non-college prime-age (ages 25-54) workers in each occupation at the two-digit SOC level\(^4\). I classify occupations as either high skill (H) or low

\(^2\)See a recent paper by Jardina, Blair, Heck and Debroy (2023) for an overview of occupational segregation for black and white workers in the U.S.

\(^3\)A recent paper by Lester, Rivers, and Topa (2021) show that referrals from business contacts primarily help high productivity workers with high incomes and a high skill level, while referrals from family and friends provide a key source of information for workers at the lower end of the income distribution, particularly in low skill markets.

\(^4\)Two-digit SOC is used to maintain a consistent classification of occupations between datasets.
skill (L) so that about half of non-college workers are employed in each. This is the categorization I’ll be working with in my model. While working with a larger number of occupations would be informative, limited observations by race in the SCE and MCSUI prevent a more dis-aggregated analysis. Figure 1 shows the percent of black and white workers employed in H occupations, illustrating the lack of decline in segregation over the past two decades and the segregation of black workers into a less productive set of occupations.

Figure 1: Percent Employed in H Occupation (non-college workers)

In order to see that this segregation cannot be fully explained by differences in the attributes of white and black workers, I want to examine segregation conditional on a set of relevant covariates. To do this, I will construct counterfactual employment distributions in which black workers are given the characteristics of white workers (that are observable in the CPS) using the
methodology laid out in Gradin (2013). See Appendix A for the full details of this decomposition technique. I find that about half of the differences in occupational choice can be accounted for by observable factors, including age, education, marital status, gender, and state. The raw percentage of black workers employed in \( H \)-type occupations average over 1995-2021 is 37\% and for white workers is 48\%, while the conditional percentage of black workers employed in \( H \)-type occupations is 43\%. The 11 percentage point gap closes by 6 percentage points, just over half.

2.5 Empirical Patterns in Referral Usage

Next, I want to examine if black and white workers have differential access to these occupations through their friend networks. Some of the most direct evidence available is through the Survey of Consumer Expectations Job Search supplement, which is a survey fielded annually each October since 2013 that focuses on job search behavior and outcomes for all individuals, regardless of their labor force status. Existing labor force surveys typically only collect information on the search behavior of the unemployed. The survey asks an expansive list of questions on the employment status and current job search of all respondents, including questions on an individual’s search effort, search methods and outcomes, and the incidence of informal recruiting methods. Demographic data is also available for respondents\(^5\). Note that this sample is a set of annual repeated cross-sections. The main monthly SCE surveys its respondents for up

\(^5\)In Faberman, Mueller, Sahin, and Topa (2022), they show that overall and for each survey year, the Job Search Supplement matches the demographics of the CPS reasonably well, with some exceptions being that the Job Search Supplement contains a higher shares of White, older, and married individuals compared to the CPS.
to 12 months. Since the Job Search Supplement draws from these respondents each October, individuals will be in the supplement only once. Here I present estimates for a sample that pools the 2013–2021 data together.

Figure 2 shows the percentage of jobs obtained by race and occupation-type. It suggests that black and white workers successfully use their social networks to obtain a job at a similar rate, but there’s a difference in access when it comes to the occupation type. Black workers are able to access low-paying jobs through their network at a slightly higher rate than white workers, and white workers are able to access higher-paying jobs through their network at a substantially higher rate than black workers.

Figure 2: Referral Usage by Race and Occupation

To establish that this relationship is not just capturing worker characteristics, I model the determinants of employed workers having found a job through a referral. I want to examine, conditional on being employed, the prob-
ability of using friends and relatives to obtain a job. The probability of success is assumed to be a logistic function where $z = 1$ if an employed worker finds a job through a friend or relative referral, and $z = 0$ if the found the job in some other way. I run a worker-level logistic regression on a dummy variable for referral usage against an interaction between indicator variables for being white and occupation type. I also control for state fixed effects, and a set of worker characteristics including education, age, gender, union status, and marital status. Then

$$P(z_i = 1 \mid e_i = 1) = \frac{\exp(\beta'x)}{1 + \exp(\beta'x)}$$

where $x$ is my set of explanatory variables and $e_i$ is an indicator of employment status. Let $p$ be the probability that a referral is used. Then

$$\text{logit}(p) = \ln \left( \frac{p}{1 - p} \right) = \beta_0 + \beta_1 H + \beta_2 \text{white} + \beta_3 (H \times \text{white}) + \text{controls}$$

Results are reported in Table 1. The positive and significant coefficient on the interaction term tells us how the likelihood of using a referral differs across groups (blacks and whites) by occupation. Here it’s positive, indicating that whites are likelier to use their friend network when obtaining $H$ type jobs than their black counterparts. Specifically, I have $\exp(1.327) = 3.77$. This means that a white person in an $H$-type job has about 3.77 times the odds of the black person using a referral of working in an $H$ job, or equivalently, a $3.77 - 1 = 2.77, 277\%$ more odds of having obtained their job through a referral.
Table 1: Regression for use of referrals

<p>| | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>H occupation</td>
<td>-0.663</td>
<td>-0.853</td>
<td>-0.979*</td>
</tr>
<tr>
<td></td>
<td>(.463)</td>
<td>(.500)</td>
<td>(.531)</td>
</tr>
<tr>
<td>White dummy</td>
<td>-0.174</td>
<td>-0.375</td>
<td>-0.407</td>
</tr>
<tr>
<td></td>
<td>(.327)</td>
<td>(.365)</td>
<td>(.374)</td>
</tr>
<tr>
<td>Interaction</td>
<td>0.746</td>
<td>1.184**</td>
<td>1.327**</td>
</tr>
<tr>
<td></td>
<td>(.501)</td>
<td>(.580)</td>
<td>(.623)</td>
</tr>
<tr>
<td>State FE</td>
<td></td>
<td></td>
<td>x</td>
</tr>
<tr>
<td>Worker Characteristics</td>
<td>x</td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>Psuedo R2</td>
<td>0.003</td>
<td>0.090</td>
<td>0.16</td>
</tr>
<tr>
<td>Obs</td>
<td>866</td>
<td>744</td>
<td>733</td>
</tr>
</tbody>
</table>

Robust standard errors are shown in parenthesis.
*\(p < 0.1\); **\(p < 0.05\)

To make these results more interpretable, I can calculate the probability that black and white workers obtained their job via a referral by occupation type. For each individual, I use the individuals observed values for all variables except occupation and race. For occupation and race, I calculate the probability of success for all combinations of occupation \(j \in \{H, L\}\) and race \(r \in \{B, W\}\) for each observation. Then I average the estimated probabilities across all observations for each race/occupation combination, and plot these results (with 90 percent confidence intervals) in Figure 3. These numbers are quite similar to what we see in the raw data, although the differences between black and white workers are larger once we control for differences in worker characteristics and location.

How robust are results to different groupings of occupations? Unfortunately, there are not enough observations to examine each 2-digit SOC code separately in the SCE. To see finer patterns, I can instead consider 3 different
groups: low, medium, and high. Low includes the bottom seven SOC codes from Table 5, high the top seven SOC codes, and medium the eight middle SOC codes. Table 2 displays summary statistics for black and white workers by these 3 occupations.

While white workers usage of referrals is more evenly spread across occupation types, black workers have a clear pattern—they rely on referrals the most for the lowest-type occupations, and the least for the highest-type occupations. Note however that for black workers, I’m relying on a small number of observations and the standard errors can become quite large.

Results for the same logistic regression that was evaluated in section 3 for the two occupations are given in Table 3.
Table 2: Referral usage by race and occupation

<table>
<thead>
<tr>
<th></th>
<th>Black</th>
<th>White</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>43.6</td>
<td>35.0</td>
</tr>
<tr>
<td></td>
<td>(10.4)</td>
<td>(4.5)</td>
</tr>
<tr>
<td>Medium</td>
<td>25.1</td>
<td>31.9</td>
</tr>
<tr>
<td></td>
<td>(5.7)</td>
<td>(2.7)</td>
</tr>
<tr>
<td>High</td>
<td>20.7</td>
<td>31.5</td>
</tr>
<tr>
<td></td>
<td>(11.7)</td>
<td>(5.0)</td>
</tr>
</tbody>
</table>

Standard errors are shown in parenthesis.

Table 3: Logistic regression: referral usage by race and occupation

<table>
<thead>
<tr>
<th></th>
<th>Black</th>
<th>White</th>
</tr>
</thead>
<tbody>
<tr>
<td>Med occupation</td>
<td>-0.834</td>
<td>-0.914</td>
</tr>
<tr>
<td></td>
<td>(0.515)</td>
<td>(0.601)</td>
</tr>
<tr>
<td>High occupation</td>
<td>-1.088</td>
<td>-1.220</td>
</tr>
<tr>
<td></td>
<td>(0.803)</td>
<td>(0.901)</td>
</tr>
<tr>
<td>White dummy</td>
<td>-0.361</td>
<td>-0.715</td>
</tr>
<tr>
<td></td>
<td>(0.459)</td>
<td>(0.511)</td>
</tr>
<tr>
<td>Med Interaction</td>
<td>0.693</td>
<td>1.198*</td>
</tr>
<tr>
<td></td>
<td>(0.566)</td>
<td>(0.659)</td>
</tr>
<tr>
<td>High Interaction</td>
<td>0.930</td>
<td>1.425</td>
</tr>
<tr>
<td></td>
<td>(0.858)</td>
<td>(0.961)</td>
</tr>
</tbody>
</table>

<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
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<th></th>
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<tbody>
<tr>
<td>State FE</td>
<td>x</td>
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</tr>
<tr>
<td>Worker Characteristics</td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>Psuedo R2</td>
<td>0.0052</td>
<td>0.1554</td>
</tr>
<tr>
<td>Obs</td>
<td>866</td>
<td>733</td>
</tr>
</tbody>
</table>

Robust standard errors are shown in parenthesis.

*\(p < 0.1\); **\(p < 0.05\)

With three different occupations, the interaction terms are no longer significant or only significant at the 10 percent level. This could be due to a lack of observations per occupational category. More data is needed to examine this question further.
Not many surveys gather information on the race of the individual offering the referral. Fortunately, the Multi-City Study of Urban Inequality (MC-SUI), conducted in 1992-1994, collects this information for individuals in three cities: Atlanta, Boston, and Los Angeles (the survey also includes Detroit, but doesn’t ask the specific jobs search questions needed for the analysis below and so this city is excluded). This study is particularly well suited for questions on race because areas with a high proportion of African American residents were oversampled. Table 4 presents the percent of same-race contacts used by black and white workers by occupation, and overall. These results are tabulated using only black or white contacts, and not some third race, although these do make up a small percentage of the contacts.

Table 4: Racial breakdown of references

<table>
<thead>
<tr>
<th></th>
<th>same race</th>
<th>other race</th>
</tr>
</thead>
<tbody>
<tr>
<td>White</td>
<td>High</td>
<td>97.0</td>
</tr>
<tr>
<td></td>
<td>Low</td>
<td>86.0</td>
</tr>
<tr>
<td></td>
<td>Overall</td>
<td>91.0</td>
</tr>
<tr>
<td>Black</td>
<td>High</td>
<td>81.1</td>
</tr>
<tr>
<td></td>
<td>Low</td>
<td>95.0</td>
</tr>
<tr>
<td></td>
<td>Overall</td>
<td>89.0</td>
</tr>
</tbody>
</table>

Data source: Multi-City Survey of Urban Inequality (MCSUI), author’s calculations

Consider the overall rate at which individuals use same-race contacts (i.e. not by occupation). Whites contact whites 91% of the time, while blacks contact whites 11% of the time. For comparative purposes, if these contact rates reflected only the population distribution in this sample, white workers would be contacted 75% of the time. This data supports the main mechanism
of this paper’s model—that individuals will, for both occupations, get referral information through same-race individuals.

I am able to conduct the same analysis done for the SCE using the data available through the MCSUI instead. While the same patterns are seen for men in the MCSUI as were seen for everyone in the SCE, the data for women in the MCSUI does not follow the same patterns. Figures 4 and 5 report the raw summary statistics as well as the predicted results from the logistic regression reported separately for men and women from the MCSUI. For comparison, these same results are reported for the SCE by gender in Figures 6 and 7. Although both men and women follow the same general pattern in the SCE, the summary statistics in particular for men are starker.

Figure 4: Men: Referral usage by race and occupation (MCSUI)
See Appendix A for separate reports by city with statistics that include the use of referral from workers that are not black or white.
2.6 Conclusion

I’ve provided some empirical evidence for differences in the use of referral networks by race and occupation. I show that occupational segregation for black and white non-college workers has been relatively stable for the previous two decades. I then make the case that differences in access to vacancy information via referrals could be an important explanatory variable when it comes to differences in occupational choice. Using the MCSUI, I can confirm that the majority of vacancy information is passed between same-race contacts for both black and white workers. Using the SCE, I find that black workers have relatively better access to lower skill and lower paying jobs via referral networks, while white workers have significantly better access to higher skill and higher paying jobs via referral networks. I’m able to see the same patterns emerge in the MCSUI, however only for men.

Since the empirical evidence for network use by race and occupation is still rather limited, these findings should be interpreted with some caution and future research is needed to confirm their robustness.

2.7 Appendix A

Occupation Categorization:
Table 5: Median & Mean Wages by SOC

<table>
<thead>
<tr>
<th>SOC</th>
<th>Description</th>
<th>Median</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>L occupations:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>35</td>
<td>Food Preparation and Serving Related</td>
<td>10.41</td>
<td>11.12</td>
</tr>
<tr>
<td>45</td>
<td>Farming, Fishing, and Forestry</td>
<td>10.86</td>
<td>12.03</td>
</tr>
<tr>
<td>39</td>
<td>Personal Care and Service</td>
<td>11.45</td>
<td>12.71</td>
</tr>
<tr>
<td>37</td>
<td>Building and Grounds Cleaning and Maintenance</td>
<td>12.01</td>
<td>13.43</td>
</tr>
<tr>
<td>41</td>
<td>Sales and Related</td>
<td>12.26</td>
<td>13.76</td>
</tr>
<tr>
<td>31</td>
<td>Healthcare Support</td>
<td>12.94</td>
<td>14.07</td>
</tr>
<tr>
<td>25</td>
<td>Education, Training, and Library</td>
<td>13.63</td>
<td>15.88</td>
</tr>
<tr>
<td>43</td>
<td>Office and Administrative Support</td>
<td>15.61</td>
<td>16.80</td>
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<td>53</td>
<td>Transportation and Material Moving</td>
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<td>H occupations:</td>
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<td>51</td>
<td>Production</td>
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<td>17.66</td>
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<td>Community and Social Services</td>
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<td>Protective Service</td>
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<td>13</td>
<td>Business and Financial Operations</td>
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<td>11</td>
<td>Management</td>
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<td>20.75</td>
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<tr>
<td>47</td>
<td>Construction and Extraction</td>
<td>19.78</td>
<td>22.02</td>
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<tr>
<td>19</td>
<td>Life, Physical, and Social Sciences</td>
<td>20.74</td>
<td>22.16</td>
</tr>
<tr>
<td>49</td>
<td>Installation, Maintenance, and Repair</td>
<td>21.43</td>
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<td>29</td>
<td>Healthcare Practitioners and Technical</td>
<td>21.49</td>
<td>23.42</td>
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<td>15</td>
<td>Computers and Mathematics</td>
<td>22.27</td>
<td>25.10</td>
</tr>
<tr>
<td>17</td>
<td>Architecture and Engineering</td>
<td>23.66</td>
<td>25.50</td>
</tr>
</tbody>
</table>

Data sources: CPS, 1995m1-2021m9, author’s calculations

**Occupational Segregation Decomposition.** Each observation belongs to a joint distribution $F(j, z, r)$ of occupations $j \in \{H, L\}$, individual characteristics $z \in \{z_1, \ldots, z_k\}$ defined over domain $\Omega_k$, and a dummy $r$ indicating group membership $r \in \{B, W\}$. The joint distribution of occupations and attributes of each group is a conditional distribution $F(j, z|r)$. The discrete density function of occupations for each group, $f^i(j)$ can be expressed as the product of two
conditional distributions:

\[ f^i(j) \equiv f(j|r = i) \]
\[ = \int_z dF(j, z|r = i)dz \]
\[ = \int_z f(j|z, r = i) \cdot f(z|r = i)dz \]

where \( i = 1 \) for whites and \( i = 0 \) for blacks. Assuming the structure of occupations for blacks \((f(j|z, r = 0))\) doesn’t depend on the distribution of attributes, I can define a counterfactual distribution \( f_z(j)\):

\[ f_z(j) = \int_z f(j|z, r = 0) \cdot f(z|r = 1)dz \]
\[ = \int_z f(j|z, r = 0) \cdot \varphi_z \cdot f(z|r = 0)dz \]
\[ = \int_z \varphi_z f(j, z|r = 0)dz \]

If blacks kept their own conditional probability of being in a given occupation, \( f(j|z, r = 0) \), but had the same characteristics of whites given their marginal distribution \( f(z|r = 1) \), then this is the density that would occur. This can be produced by properly re-weighting their original distribution.

Using Bayes’ Theorem: \( f(z|r = i) = \frac{Pr(r=i|z)Pr(z)}{Pr(r=i)} \). Then

\[ \varphi_z = \frac{f(z|r = 1)}{f(z|r = 0)} = \frac{Pr(r = 0)Pr(r = 1|z)}{Pr(r = 1)Pr(r = 0|z)} \]

This is the unconditional probabilities of group membership (a constant) times
the conditional probabilities that can be obtained by pooling the samples of black and white workers and estimating a logit model for the probability of being white conditional on $z$, i.e. $Pr(r = 1|z) = \frac{\exp(z\hat{\beta})}{1+\exp(z\hat{\beta})}$ where $\hat{\beta}$ is the vector of estimated coefficients.

Allow $S(j|z) \equiv S(f(j|r = 1), f_z(j))$ to denote the conditional segregation index. This is the amount of unexplained segregation that remains once I’ve controlled for observable characteristics.

**MCSUI: by city**

Atlanta has 508 observations, 168 white. Los Angeles has 681 observations, 235 white. Boston has 424 observations, 206 white.

| Racial breakdown of friend/family references (Atlanta): |
|---------------------------------|---------------------------------|---------------------------------|
|                                 | same race                       | other race (white/black)        | other race (other) |
| white                           |                                 |                                 |                  |
| (high occ)                      | 1                               | 0                               | 0                |
| (low occ)                       | 99.6                            | 0.4                             | 0                |
| black                           |                                 |                                 |                  |
| (high occ)                      | 76.4                            | 16.2                            | 7.3              |
| (low occ)                       | 1                               | 0                               | 0                |

Source: Multi-City Survey of Urban Inequality (MCSUI), author’s calculations
### Racial breakdown of friend/family references (Los Angeles):

<table>
<thead>
<tr>
<th></th>
<th>same race</th>
<th>other race (white/black)</th>
<th>other race (other)</th>
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<td>(high occ)</td>
<td>87.0</td>
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<td></td>
<td>(low occ)</td>
<td>80.6</td>
<td>19.0</td>
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<tr>
<td>black</td>
<td>(high occ)</td>
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<td>0</td>
</tr>
<tr>
<td></td>
<td>(low occ)</td>
<td>95.6</td>
<td>2.0</td>
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</tbody>
</table>

Source: Multi-City Survey of Urban Inequality (MCSUI), author’s calculations

### Racial breakdown of friend/family references (Boston):

<table>
<thead>
<tr>
<th></th>
<th>same race</th>
<th>other race (white/black)</th>
<th>other race (other)</th>
</tr>
</thead>
<tbody>
<tr>
<td>white</td>
<td>(high occ)</td>
<td>99.8</td>
<td>0.1</td>
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<td></td>
<td>(low occ)</td>
<td>79.5</td>
<td>19.2</td>
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<tr>
<td>black</td>
<td>(high occ)</td>
<td>48.1</td>
<td>51.7</td>
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<tr>
<td></td>
<td>(low occ)</td>
<td>79.1</td>
<td>16.4</td>
</tr>
</tbody>
</table>

Source: Multi-City Survey of Urban Inequality (MCSUI), author’s calculations

## 2.8 Bibliography


DiMaggio, Paul, and Filiz Garip. “How network externalities can exacerbate


3 Chapter 2: A Model of the Labor Market with Homophilic Referral Networks

3.1 Abstract

This chapter studies the impact of racially segregated referral networks on inequality and aggregate welfare. I incorporate a referral-based matching function into a standard search and match model with occupational choice, heterogeneous ability levels, free entry, and wages determined by Nash bargaining. Social segregation can lead to differences in occupational choice by race, and thus wage and employment inequality, in the steady state. After calibrating the model to examine black and white workers in the United States, the estimates show that racially biased networks alone can generate a black-white wage gap of 1.66 percent and an employment gap of 0.74 percentage points. Moving from the segregated to the desegregated steady state harms the majority white workers while helping the minority black workers, resulting in a decrease in aggregate welfare.

3.2 Introduction

In this chapter, I will show that social divisions combined with employment divisions can generate a feedback loop that reinforces a stable path for occupational segregation by race. I develop a model to rationalize patterns in the data and examine inequality and welfare effects. The model does not include any discrimination by employers and does not rely on any heterogeneity between racial groups beyond their networks to generate racial differences in outcomes.
I embed a matching function that incorporates a referral network with racial homophily into a standard search and match model with multiple occupations, heterogeneous ability levels, free entry, and wages determined by Nash bargaining. Unemployed workers must choose which occupation they want to search in. The more friends a worker has who are employed in the occupation they are searching for a job in, the likelier they are to hear about an open vacancy and become employed. However, the occupation that fully exploits an individuals’ referral network may not be the same occupation that fully exploits their productive advantage. This generates a possible trade-off between the rate at which an individual finds a match and the productivity of that potential match. I am able to derive group differences endogenously even when groups share identical fundamentals, with initial differences in access to vacancy information perpetuated in equilibrium by induced differences in occupational choice between racial groups.

I calibrate the model by matching the patterns observed in the data. I am able to match the amount of occupational segregation observed in the data, as well as the rate of referral usage by race and occupation. Under the same set of parameter values, the model also supports a desegregated equilibrium, allowing for a comparative analysis and policy recommendations. I find that socially segregated networks alone can generate a 1.66% difference in wages between black and white workers and a 0.74 percentage point gap in employment. Welfare analysis reveals that moving to the desegregated steady state would on average harm white workers while helping black workers. I argue that evaluation of programs such as affirmative action should include network effects.
3.3 Literature

There is a small literature examining social networks as a mechanism for group educational and occupational segregation, including Buhai and van der Leij (2023) and Pothier (2018). Buhai and van der Leij show that occupational segregation can be supported in an equilibrium when individuals are more likely to form with-in group ties. They examine segregation in terms of educational choices, leading to differences in occupation, as a result of social color homophily via a static four-stage partial-equilibrium model where workers choose their education in the first stage. They then form network ties, followed by the job search process and finally earning a wage and consumption. Their model results lead to complete segregation, i.e. at least one social color choosing only one educational path/occupation. They also find that the segregated equilibrium is always socially optimal. These results could be driven by not allowing for mismatch between a workers educational choices and their innate ability. In contrast, the model in this paper supports partial segregation and incorporates a notion of mismatch that allows for the possibility that the desegregated steady state admits higher aggregate welfare, although I do not find this to be the case. Pothier also focuses on human capital investments and focuses on the allocative implications of segregation. The model incorporates a market with asymmetric information and worker-specific skill type that effects the costs to specializing in a particular occupation. A key component of Pothier’s model is the firm’s inability to observe the workers’ skill-type, so that wage contracts cannot be written contingent on a workers’ productivity. This generates another externality where workers do not internalize the decreased productivity generated by a
mis-allocation of talent.

While the primary emphasis of my paper is on racial homophily, the analytic framework could be applied to other types of social groups as well, for example by gender or socioeconomic status. A recent paper by Chetty et al. (2022) found that two thirds of differences in upward economic mobility across communities can be accounted for by differences in a measure of social capital that captures the amount of homophily by socioeconomic status.

Topa (2001) uses neighborhood interactions in job search to explain the concentration of unemployment across neighborhoods in Chicago. These empirical results are consistent with theoretical results of Calvo-Armengol and Jackson (2004), who develop a model where agents gather job information through their networks. I am able to generate higher unemployment within one group using a different mechanism, where a particular group of workers rationally select into an occupation with a higher separation rate.

More recently, Galenianos (2021) examines hierarchical referral networks. In this paper, there are type-A workers who have a higher probability of forming a match when meeting a firm and potentially higher productivity on the job than type-B workers. This leads to workers of both types having the majority of their links with type-A workers and type-A workers benefit the most from the use of referrals. This type of structure then exacerbates the already existing inequality between type-A and type-B workers. This contrasts with the literature’s usual assumption of an exogenously given and homophilous network structure (an assumption I maintain in this paper). Galenianos also requires
initial group differences in productivity, which I will not require in my model although the model could accommodate and examine these types of dynamics as well. DiMaggio and Garip (2012) also examine how networks can exacerbate inequality when individual differences are compounded by social networks.

The behaviors generated by the model in this paper can also be related to the literature on statistical discrimination. The statistical discrimination literature similarly derives group differences endogenously even when groups share identical fundamentals, and tends to generate multiple equilibria. Statistical discrimination models rely on the idea of “self-fulfilling prophecies”, which refers to when an employers adverse prior beliefs about a group’s skill levels are self-confirming in equilibrium. While the statistical discrimination literature generates these patterns using differences in beliefs, this model is able to generate these patterns using differences in access to vacancy information. Initial differences in access to vacancy information are perpetuated in equilibrium by induced differences in occupational choice between racial groups.

3.4 Model Environment

The model is designed to rationalize persistent differences by race in occupational choice through their social network and examine questions related to inequality and aggregate welfare. Time is continuous and the labor market is in steady state.

Workers: There is a measure one of infinitely lived workers who are heterogeneous in ability and race. They are either employed in occupation
$j \in \{H,L\}$ or unemployed and searching in occupation $j^6$. I consider two races $r \in \{W,B\}$. The relative population sizes of each race are denoted by $\tau^r \in [0,1]$, with $\sum_r \tau^r = 1$. Ability types are indexed by $x$, and are permanent and observable. Denote $G(\cdot)$ the distribution of ability with corresponding density $g(\cdot)$. Note that the distribution of ability is the same for each group. Consequently, any occupational segregation observed in equilibrium will be a result of strategic decisions made by workers, rather than an assumed disparity in productivity among individuals from different social groups. Each worker is endowed with 1 unit of labor. There is no on-the-job search. Workers have risk neutral preferences and discount the future at rate $\rho \in (0,1)$.

**Firms:** A free entry condition determines the measure of firms. These firms either produce output $y_j(x)$, $j \in \{H,L\}$, when matched with a worker of ability $x$, or post vacancy $v_j$ for workers of any type. Employers are risk neutral and also discount at rate $\rho$.

**Production Tech:** There are two types of production technologies that define two types of occupations, and their outputs are perfect substitutes. Technology used at low-skill occupations is not a function of worker ability.

---

$^6$Using occupations to define separate labor markets is generally a relevant search criterion for both workers and firms. Usually, firms post vacancies for certain qualifications in terms of occupation or education, and workers primarily look for jobs in their occupation. Evidence shows that occupational mobility is generally quite low, such a matching process is in line with this.
Technology is not a function of worker race. Specifically,

\[ y_j(x) = \begin{cases} 
A_L & \text{if } j = L \\
A_Hx & \text{if } j = H 
\end{cases} \]

**Matching Technology:** Every worker is linked with a measure of other workers. Assume the size of each worker’s network is the same. A worker’s employment opportunities in a particular occupation will depend on how many of their links are employed in that occupation. Having a continuum of links means that the employment rate of a worker’s social contacts reflects the aggregate due to the law of large numbers.

The rate at which workers receive information from someone of the same race versus the other race depends on two exogenous parameters. These include in-group bias \( \gamma^r \in [0, 1] \) and population share \( \tau^r \in (0, 1) \). When \( \gamma^r = 1 \), we are operating in a world of complete homophily or social segregation, with workers only receiving information from individual’s of the same race. When \( \gamma^r = 0.5 \), there is no bias and worker’s receive information from each race at a rate proportional to their population size \( \tau^r \). I generally won’t be interested in \( \gamma^r < 0.5 \). Then the expected share of same-race contacts is

\[ \phi^r = \frac{\tau^r \gamma^r}{\tau^r \gamma^r + \tau^r (1 - \gamma^r)} \]

The rate at which workers hear about occupation-specific vacancy in-

\[ \text{For example, if } \gamma^r = 0.5 \text{ and 75% of the population is white, both black and white workers would expect to get information from white individuals 75% of the time.} \]
formation depend on $\phi^r$ and a set of endogenous variables, occupational choice for both black and white workers and the occupation-specific employment rates of these groups. Allow $a^r_j$ to denote the percent (or allocation) of individuals of race $r$ that are searching or working in $j$ occupation. The percent of employed ($\bar{e}^r_j$) and unemployed ($\bar{u}^r_j$) contacts either working or searching in occupation $j$ for an individual of race $r$ are:

$$
\bar{e}^r_j = \phi^r a^r_j e^r_j + (1 - \phi^r) a^\neg r_j e^\neg r_j,
\bar{u}^r_j = \phi^r a^r_j u^r_j + (1 - \phi^r) a^\neg r_j u^\neg r_j
$$

where $\neg r$ denotes the ‘other’ race. These are simply weighted averages of the endogenous employment rates by race and occupation ($e^r_j$) and the endogenously determined allocation of individuals working/searching in occupation $j$ by race ($a^r_j$), where the weights are determined by the exogenous given homophily parameter ($\gamma^r$) and population size ($\tau^r$).

Vacancy creation occurs in two ways: a new firm enters the market (creating a standard vacancy), or an already existing firm employing a worker expands at rate $\kappa_j$. If a match is formed, the firm immediately sells the position off so that each firm maintains employment of only one worker. As in Galenianos (2014), expansion can be understood in two ways: an entrepreneur partners with an existing firm to fill a new role, or the firm identifies a profitable opportunity but sells the new position due to decreasing returns.

When an expansion occurs, one of the links of the incumbent worker is contacted at random. If the link is unemployed and searching in occupation $j$ then he is hired by the firm and begins work next period; if the link is em-
ployed in occupation \( j \), he can potentially receive the vacancy information and instantaneously pass it along to one of his own contacts; otherwise the referral opportunity is lost and it becomes a market vacancy next period. The rate at which the unemployed worker is referred to a job is

\[
p^r_j \equiv \kappa_j (\bar{e}_j^r)^\Gamma_j
\]

The number of meetings is determined by the effective number of employed contacts (\( \bar{e}_j^r \)), the expansion rate (\( \kappa_j \)), and a measure of nonlinear information dispersion (\( \Gamma_j \)). Cappellari and Tatsiramos (2015) find some evidence of potential convex/nonlinear network effects when looking at the relationship between the number of employed workers in an individual’s friend network and the job finding rate\(^8\). Allowing for \( \Gamma_j \neq 1 \) takes into account potential non-linearities in this relationship. Note that this referral rate does not depend on the worker’s ability level \( x \). Then the flow of meetings via referral by race and occupation is:

\[
P^r_j = u^r_j p^r_j
\]

Note that we can also define the job filling rate through referrals as the flow meeting of referrals divided by the total number of referral vacancies:

\[
k^r_j = \frac{u^r_j (\bar{e}_j^r)^\Gamma_j}{a_j^r e_j^r + a_j^{\gamma r} e_j^\gamma}
\]

\(^8\)In particular, they find that having one employed friend increases the job finding probability by 1.6 p.p., having two employed friends increases it by 4.9 p.p., and having three increases it by 11.1 p.p.
Incorporating $e_j^r$ into the matching function generates an externality when workers choose to work and search in occupation $j$, since doing so increases the likelihood that all other workers (and in particular those of race $r$) searching in occupation $j$ can hear about vacancy information through their network. This externality is the key source of the multiplicity of equilibria in this model. In particular, we have strategic complements—each agent is more willing to take an action (searching in $j$) when other agents are doing so.

For $\Gamma_j \neq 1$, the relationship between the number of employed contacts you have in an industry and the likelihood of hearing about vacancy information is nonlinear, more in line with the behavior of the network matching function derived in Calvo-Armengol and Zenou (2005). When $\Gamma_j > 1$, there are increasing returns to the relevant employed network size. This concept refers to the idea that output proportionally increases more than input as positive feedback mechanisms are triggered. As the player (in this case the worker) ahead moves further, the player that is behind, in turn, loses further advantages. Increasing returns is an important component found across various phenomena that past studies have used to explain the diffusion pattern of some technologies. For example, direct and indirect network effects (Farrell and Saloner (1985), David (1985), and Katz and Shapiro (1986)), self-fulfilling expectations (Besen and Farrell (1994)), and learning effects (Dobusch and Schüssler (2012)).

**Proposition 4.1.** The referral component of the job finding rate $p_j^r$ is decreasing in unemployment $u_j^r$ and $u_{j-r}^r \ \forall j, r$, therefore increasing in employment, i.e. \( \frac{\partial p_j^r}{\partial e_j^r} > 0 \) and \( \frac{\partial p_j^r}{\partial e_{j-r}^r} > 0 \) \ \forall j, r. \) Assuming $\Gamma_j$ is not too large, the referral job filling rate $k_j^r$ is increasing in unemployment $u_j^r$ and $u_{j-r}^r \ \forall j, r$, therefore decreasing in
employment, i.e. $\frac{\partial k_j}{\partial e_j} < 0$ and $\frac{\partial k_j}{\partial e_j} < 0$ $\forall j, r$.

**Proof.** See Appendix B.

Let $v_j$ denote the number of vacancies in occupation $j$. Vacancies are not targeted to a particular ability type $x$ or race $r$. The flow of meetings in the market between a vacancy in industry $j$ and a worker of race $r$ searching in industry $j$ is determined by a Cobb-Douglas matching function:

\[
M_j = \theta_j (v_j)\eta (\tilde{u}_j)^{(1-\eta)}
\]
\[
\tilde{u}_j = \sum_r a_j^r \tau^r u_j^r
\]

with $\theta_j > 0$ and $\eta \in (0, 1)$ The market job finding rate $f_j$ and market vacancy filling rate $q_j$ are:

\[
f_j = \frac{M_j}{\tilde{u}_j} = \theta_j (v_j)^\eta (\tilde{u}_j)^{-\eta}, \quad q_j = \frac{M_j}{v_j} = \theta_j (v_j)^{\eta - 1}(\tilde{u}_j)^{1-\eta}
\]

The matching function is then given by

\[
m_j^r = M_j + P_j^r
\]

**Proposition 4.2.** The aggregate matching function exhibits decreasing returns to scale.

**Proof.** See Appendix B.
Intuitively, if we consider a proportional increase in the number of unemployed and the number of vacancies, labor market tightness remains the same and so the standard Cobb-Douglas component of the matching function maintains the same level of efficiency. However, the number of employed links offering referrals is lowered and so the meeting rate through referrals is lowered. This corresponds to a decrease in the efficiency of the referral portion of the matching function, and therefore the aggregate matching function.

3.5 Steady State Equilibrium

Occupational choice will obey a threshold rule: if a worker with ability \( x \) finds it optimal to search and work in occupation \( H \), then so will workers with a higher ability level. Then there exists thresholds \( x^*_r \) such that for all workers from group \( r \in \{B,W\} \) with \( x > x^*_r \), they search in occupation \( H \), and for all workers with \( x \leq x^*_r \), they search in occupation \( L \). Define the following sets: \( x^*_r H = \{ x | x > x^*_r \} \) and \( x^*_r L = \{ x | x \leq x^*_r \} \). At times, it is only necessary to keep track of the portion of the population of race \( r \) searching in H or L (but not their ability type), previously denoted as \( a^*_r j \), which can be defined by integrating over density \( g(\cdot) \) as \( a^*_j = \int_{x^*_r} g(x) dx \).

Let \( E^*_j \) denote the value of expansion for a firm in occupation \( j \) with a worker of race \( r \). Expansions occur at rate \( \kappa_j \), and are sold off with incumbent firms receiving share \( \alpha \in [0,1] \) of the value. Either a match is made through the network immediately, or the referral process fails and search through the
market begins.

\[
E^r_j = V_j + \frac{\phi^r u^r_j k^r_j}{\bar{u}^r_j} \int_{x^r_j} \left[ (J^r_j(x) - V^r_j) \right] g(x)dx \\
+ \frac{(1 - \phi^r) u_j^r (1 - k^r_j)}{\bar{u}^r_j} \int_{x^r_j} \left[ (J^r_j^{-r}(x) - V^r_j) \right] g(x)dx
\]

where \( J^r_j(x) \) is the value of a match to the firm with a worker of race \( r \) type \( x \) in occupation \( j \), \( V_j \) is the value of vacancy in occupation \( j \), and \( k^r_j \) is capturing the probability of a match with a race \( r \) individual occurring. Finally, from the perspective of the employed worker, \( \phi^r a^r_j u^r_j / \bar{u}^r_j \) percent of my contacts are same-race and \( (1 - \phi^r) a^{-r} u^{-r}_j / \bar{u}^r_j \) percent are the other race (note that \( a^r_j \) is captured by the integral).

Allow \( W^r_j(x) \) denote the value of a match to a worker, and \( U^r_j(x) \) denote the value of unemployed search to a worker of race \( r \) type \( x \) in occupation \( j \). The following value functions define the worker and firm problems:

\[
\rho V^r_j = -c^r_j + \sum_r \tau^r_j u^r_j \int_{x^r_j} \left[ q^r_j (J^r_j(x) - V^r_j) \right] g(x)dx 
\]

\[
\rho J^r_j(x) = y^r_j(x) + \kappa^r_j \alpha E^r_j - w^r_j(x) + s_j \left[ V^r_j - J^r_j(x) \right] 
\]

\[
\rho W^r_j(x) = w^r_j(x) + s_j \left[ U^r_j(x) - W^r_j(x) \right] 
\]

\[
\rho U^r_j(x) = z^r_j + (f^r_j + p^r_j) \left[ W^r_j(x) - U^r_j(x) \right] 
\]

where \( U^r_j(x) = \max \{ U^L_j(x), U^R_j(x) \} \)
where \( c_j \) is the vacancy opening cost in occupation \( j \), \( s_j \) is the rate at which a match in occupation \( j \) is destroyed, and \( z_j \) is the flow value of unemployment.

The assumption that search through referral is costless for firms implicitly assumes that the incumbent worker who offers the referral resolves uncertainty about the match quality. Thus the firm doesn’t have to go through costly hiring activities, such as advertising vacancies, interviewing, and screening. This mirrors the findings of Montgomery (1991), who demonstrated that profit-maximizing firms can exploit social networks to screen job applicants without incurring costs.

Define match surplus as \( S^r_j(x) = J^r_j(x) + W^r_j(x) - U^r_j(x) - V_j \). With Nash bargaining, free entry, and worker bargaining power equal to \( \beta \), I solve for

\[
W^r_j(x) - U^r_j(x) = \beta S^r_j(x)
\]

\[
J^r_j(x) = (1 - \beta) S^r_j(x)
\]

The Nash bargaining solution along with free entry and my surplus equation gives

Free entry implies \( V_j(x) = 0 \ \forall j, x \), so that the value of an expansion to a firm
can be written as

\[ E^r_j = \frac{\phi^r u^r_j k^r_j}{\bar{u}^r_j} \int_{x^r_j} (1 - \beta) S^r_j(x) g(x) dx + \frac{(1 - \phi^r)u^r_j k^r_j}{\bar{u}^r_j} \int_{x^r_j} (1 - \beta) S^{-r}_j(x) g(x) dx \]

\[ \equiv \bar{S}^r_j \]

Free entry also gives us

\[ c_j = \sum_r \frac{r^r u^r_j}{\bar{u}_j} \int_{x^r_j} \left[ q_j (1 - \beta) S^r_j(x) \right] g(x) dx \]  

(10)

The value function for surplus is:

\[ \rho S^r_j(x) = y_j(x) - z_j - S^r_j(x)(s + \beta(f + p^r_j)) + \alpha \kappa S^r_j \]  

(11)

An existing match generates \( y_j(x) \) units of output. If the match separates, the value of the firm falls to zero and the worker becomes unemployed, getting \( z_j \). They become employed again at rate \( f_j + p^r_j \) and keep a share \( \beta \) of the match surplus. At rate \( (1 - s_j) \), the match is maintained next period. Finally, there’s the surplus generated by the potential expansion and use of the current worker’s network. From eq (4), we have

\[ (\rho + s_j)(1 - \beta)S^r_j(x) = y_j(x) - W^r_j(x) + \alpha \kappa_j \bar{S}^r_j \]

Solving for wages yields:

\[ W^r_j(x) = y_j(x) + \alpha \kappa_j \bar{S}^r_j - (1 - \beta)(s_j + \rho)S^r_j(x) \]  

(12)
Workers benefit from how productive the match is as well as the value of their network to the firm, while firms keep some portion of the surplus generated by the match for themselves.

I will derive four expressions summarizing the steady state equilibrium: the job creation curve, the wage equation, the unemployment equation, and a condition representing how agents chose whether to search for low or high skilled occupation.

Steady state surplus equation:

\[
S_r^r(x) = \frac{y_j(x) - z_j + \alpha \kappa_j \bar{S}_j}{\rho + s_j + \beta (f_j + p_j^r)} + s_j + \beta (f_j + p_j^r)
\] (13)

**Job Creation Curve**: the free entry condition, along with (3) and (4), yield the job creation curve:

\[
c_j = \sum_r \tau_r \frac{w_j^r}{u_j} \int_{x_j} \left( q_j \frac{y_j(x) - w_j^r(x) + \alpha \kappa_j \bar{S}_j}{\rho + s_j} \right) g(x) dx
\] (14)

**Steady State Wages**: Plugging the steady state equation for surplus into (12) yields

\[
w_j^r(x) = y_j(x) + \alpha \kappa_j \bar{S}_j - (1 - \beta) (s_j + \rho) \left[ \frac{y_j(x) - z_j + \alpha \kappa_j \bar{S}_j}{\rho + s_j + \beta (f_j + p_j^r)} \right]
\] (15)

**Steady State Employment**: The steady state conditions for flow into and out of unemployment and employment, conditional on a worker searching/working
in occupation \( j \), are:

\[
\nu^*_j = \frac{s_j}{f_j + p^*_j + s_j}
\]

(16)

\[
e^*_j = \frac{f_j + p^*_j}{f_j + p^*_j + s_j}
\]

(17)

Note that since the job finding rate through both the market and the network does not depend on your ability type \( x \), employment rates will be the same for all \( x \) within each race and occupation.

**Occupational Choice** When unemployed, workers endogenously choose whether to search for high or low skilled occupations. They make this decision by maximizing over the future discounted value of both options. In steady state, this decision, laid out in equations (6) and (7), (with substitution from eq (5)), gives me:

\[
\rho U^*_j(x) = \frac{(f_j + p^*_j)w^*_j(x) + (\rho + s_j)z_j}{\rho + f_j + p^*_j + s_j}
\]

So that the choice becomes

\[
\max_j \rho U^*_j(x) = \max_j \left[ \frac{(f_j + p^*_j)w^*_j(x) + (\rho + s_j)z_j}{\rho + f_j + p^*_j + s_j} \right]
\]

(18)

This choice function includes both individual endowments and the extent to which one’s network have already chosen a particular occupation. Note that
the desegregated steady state (where black and white workers make the same occupational choices) is always supported in equilibrium. When occupational choices are the same for black and white workers, the referral rates through the network (captured by $p^r_j$) are the same as well. Then there are no meaningful asymmetries between black and white workers, and the desegregated steady state is maintained.

Equations (14), (15), (16), and (18) then determine the steady state equilibrium.

### 3.6 Calibration

In this section I calibrate the model to uncover the values of the structural parameters required to generate the patterns we observe in the data. Table 6 lists the parameter estimates. The following section provides details on how these parameters were estimated.

**Occupation categorization**: Occupations group jobs based on the task or skill content of their employees, while industries group jobs based on the product category of their output. This distinction makes occupations a better dimension along which to divide vacancies into low- and high-skilled. Occupations are ranked by skill level, which is approximated by the mean log wage of non-college workers in each occupation. See Appendix A for a table of 2-digit occupations and the calculated median and mean wage.

**Separation rates**: For simplicity I group unemployed and not in the labor force into one group, the non-employed. While these are distinct labor
Table 6: Calibration

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Source</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta$</td>
<td>0.50</td>
<td></td>
<td>worker bargaining power</td>
</tr>
<tr>
<td>$\rho$</td>
<td>0.0033</td>
<td>(monthly)</td>
<td>discount rate</td>
</tr>
<tr>
<td>$\eta$</td>
<td>0.565</td>
<td>Galenianos (2014)</td>
<td>elasticity matching function</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>0</td>
<td>see text</td>
<td>expansion surplus share</td>
</tr>
<tr>
<td>$c_{H, L}$</td>
<td>0.13 , 0.10</td>
<td>CPS</td>
<td>vacancy posting cost</td>
</tr>
<tr>
<td>$s_{H, L}$</td>
<td>0.034 , 0.043</td>
<td>CPS</td>
<td>separation rate</td>
</tr>
<tr>
<td>$\gamma_{B, W}$</td>
<td>0.96 , 0.77</td>
<td>MCSUI</td>
<td>homophily rate</td>
</tr>
<tr>
<td>$\tau_{B, W}$</td>
<td>0.25 , 0.75</td>
<td>MCSUI</td>
<td>population share</td>
</tr>
<tr>
<td>$z_{H, L}$</td>
<td>0.055 , 0.208</td>
<td></td>
<td>flow utility of unemp</td>
</tr>
<tr>
<td>$A_{H, L}$</td>
<td>0.761 , 1.254</td>
<td></td>
<td>production tech</td>
</tr>
<tr>
<td>$\theta_{H, L}$</td>
<td>0.042 , 0.048</td>
<td></td>
<td>market matching tech</td>
</tr>
<tr>
<td>$\kappa_{H, L}$</td>
<td>0.444 , 0.103</td>
<td></td>
<td>firm expansion rate</td>
</tr>
<tr>
<td>$\Gamma_{H, L}$</td>
<td>2.411 , 1.176</td>
<td></td>
<td>nonlinear matching tech</td>
</tr>
<tr>
<td>$\sigma_x$</td>
<td>0.368</td>
<td></td>
<td>sd of ability</td>
</tr>
</tbody>
</table>

market statuses, Elsby and Shapiro (2012) and Juhn, Murphy, and Topel (1991, 2002) argue the difference is unclear over the long-run. Those not in the labor force are very similar to the unemployed because they have long spells without jobs and not many employment opportunities. Since I’m focusing on the steady state/long-run behavior, it is reasonable to group these individuals together. Beyond this, Fallick and Fleischman (2004) and Hornstein et al. (2014) show that the number of out-of-the labor force individuals who transition to employment is greater than the number of unemployed people who transition to employment in a given month, again indicating that it would be reasonable to treat these individuals as one group. For the separation rates, I calculate flows out of employment and into non-employment by occupation type using IPUM-CPS, and find that $s_L = 0.043$ and $s_H = 0.035$. 

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**Vacancy posting costs:** Vacancy costs are meant to capture the cost of recruitment, which is incurred before a match is formed, and encompasses the cost of advertising vacancies, interviewing, and screening. There is evidence that vacancy posting costs vary by skill\(^9\). Barron, Berger, and Black (1997) use the 1982 Employment Opportunity Pilot Project survey of 5700 employers, and provide evidence for the time and costs involved in recruiting workers. In particular, they estimate that the average labor cost of hiring one worker is 3% to 4.5% of quarterly wages of a new hire. Here I assume it’s 3.5%.

Beginning with a redesign of the survey in 1994, three new questions were added in rotation groups 2–4 and 6–8 that asked individuals who reported being employed in the previous month as well as the current month whether they still worked for the same employer (empsame), whether their job activities and duties were the same, and whether the occupation and work activities reported last month were still accurate for the current month. Fallick and Flesichman (2004) were among the first to use these variables to measure labor flow dynamics in the CPS. If someone reports being out of the labor force or unemployed in the initial month but employed in the next month, they are counted as a new hire. Another group of newly hired workers are those who are employed from one month to the next but who switch employers. These hires can be determined by individuals who report that their employers are not the same as in the previous month. Using low-skilled real monthly earnings as the numeraire, I have \(c_L = 0.10\) and \(c_H = 0.14\).

\(^9\)For example, according to Dube et al. (2010), the estimated replacement costs in California amount to $2,500 for blue-collar workers and $8,800 for professional workers (both in 2013 dollars).
**Bargaining Power:** Typically, scholarly literature assigns a value of 0.50 to represent bargaining power between workers and firms so that it is evenly divided between the two actors. For the baseline model, I will also set bargaining power to 0.50.

**Expansion surplus share:** In the baseline model I set $\alpha$, which dictates the share of surplus kept by the expanding firm after a successful expansion, to zero. I will show that when I recalibrate the model assuming that the true value for $\alpha$ is positive, this increases wage inequality. In that sense, the baseline results can be viewed as a conservative estimate for the wage inequality produced by my proposed mechanism.

**Population Size $\tau^r$ and in-group bias $\gamma^r$:** Using the known values for $\tau^r$ from the MCSUI, I can back out values for $\gamma^r$ that coincide with the rate at which individuals use same-race contacts in the MCSUI data:

\[
\frac{\tau^W \gamma^W}{\tau^W \gamma^W + \tau^B (1 - \gamma^W)} = .91 \implies \gamma^W = .77
\]

\[
\frac{\tau^B \gamma^B}{\tau^B \gamma^B + \tau^W (1 - \gamma^B)} = .89 \implies \gamma^B = .96
\]

Figure 8 displays how in-group bias $\gamma^r$ and the percent of same-race contacts $\phi^r$ vary together, holding $\tau^r$ fixed. With $\gamma^r = 0.5$, the probability of using a same-race tie is simply the population size $\tau^r$. Since $\tau^B < \tau^W$, but $\phi^B$ is very nearly the same as $\phi^W$, a larger value for $\gamma^B$ relative to $\gamma^W$ is implied.

**Ability distribution ($x$):** The remaining parameters are calibrated to fit moments observed in the CPS and SCE. The ability index $x$ is used
to characterize the heterogeneity of workers and identify variables related to that heterogeneity (in particular, wages and occupational choice). Nowhere in the model does \( x \) appear alone; it does not mean anything by itself, and needs to be interacted with the firm’s production technology \( A_H \) to have an interpretation. I use a log-normal distribution to model ability and normalize the mean \( \mu_x \) to 0.5 arbitrarily, as it will have no effect on the results once \( A_H \) is appropriately calibrated. However, the variance of \( x \) is important for capturing the wage distribution in the high-type occupation. I use the 90th percentile wages for high-type occupations from the CPS (with average low-skill wages as the numeraire) as a calibration target to discipline the value for \( \sigma_x \).

Matching and production tech \( (\kappa_j, \Gamma_j, \theta_j, A_j, z_j) \): I use these 10 additional parameters to match 10 additional moments from the data. In
particular, I match the percentage of black and white individuals employed in high and low occupations, the rate at which black and white individuals use referrals by occupation, as well as job finding rates by race, and average wages by occupation.

Matching efficiency $\theta_j$ measures the productivity of the process for matching unemployed workers to open vacancies. Allowing for heterogeneity by occupation helps me capture differences that affect the frictions characterizing the market matching process\textsuperscript{10}. I find that the matching efficiency for $H$ occupations is lower than it is for $L$ occupations. Barnichon and Figura (2015) point out that “hiring for high-skill occupations may be more time-consuming than hiring for low-skill occupations. As a result, low skill occupations may display a higher number of new matches per unit of time (for a given number of job seekers and job openings), i.e., a higher matching efficiency.” This is reflected in my calibrated results here.

Unemployment flows $z_j$ measure the value of being unemployed. I find that unemployment flows are lower in $H$ occupations than $L$ occupations, potentially reflecting the higher search costs demanded by $H$ occupations.

3.7 Results

I am able to hit all of my targeted moments for the segregated steady state, and then examine what the desegregated steady state would look like in a world gov-\textsuperscript{10}For example, differences in skill requirements, search channels, search intensity, screening problems, etc.
erned by the same fundamentals. It is important to highlight that the model can generate endogenous differences between two otherwise identical groups.

Table 7 displays the targeted moments for the segregated steady state, as well as those moments for the model-generated desegregated steady state. Average wages in the low-type occupation are used as the numeraire.

<table>
<thead>
<tr>
<th></th>
<th>Data</th>
<th>Targeted</th>
<th>Segregated</th>
<th>Desegregated</th>
</tr>
</thead>
<tbody>
<tr>
<td>% B employed in $H$</td>
<td>37%</td>
<td>Y</td>
<td>37%</td>
<td>45%</td>
</tr>
<tr>
<td>% W employed in $H$</td>
<td>48%</td>
<td>Y</td>
<td>48%</td>
<td>45%</td>
</tr>
<tr>
<td>job-finding rate (B)</td>
<td>0.10</td>
<td>Y</td>
<td>0.10</td>
<td>0.0998</td>
</tr>
<tr>
<td>job-finding rate (W)</td>
<td>0.10</td>
<td>Y</td>
<td>0.10</td>
<td>0.0998</td>
</tr>
<tr>
<td>mean wages (H)</td>
<td>1.39</td>
<td>Y</td>
<td>1.39</td>
<td>1.395</td>
</tr>
<tr>
<td>90th percentile wages (H)</td>
<td>2.22</td>
<td>Y</td>
<td>2.22</td>
<td>2.26</td>
</tr>
<tr>
<td>mean wages (L)</td>
<td>1.00</td>
<td>Y</td>
<td>1.00</td>
<td>1.001</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Data</th>
<th>Targeted</th>
<th>Segregated</th>
<th>Desegregated</th>
</tr>
</thead>
<tbody>
<tr>
<td>% jobs from network:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Black (L):</td>
<td>35%</td>
<td>Y</td>
<td>35%</td>
<td>32%</td>
</tr>
<tr>
<td>Black (H):</td>
<td>22%</td>
<td>Y</td>
<td>22%</td>
<td>30%</td>
</tr>
<tr>
<td>White (L):</td>
<td>32%</td>
<td>Y</td>
<td>32%</td>
<td>32%</td>
</tr>
<tr>
<td>White (H):</td>
<td>33%</td>
<td>Y</td>
<td>33%</td>
<td>30%</td>
</tr>
</tbody>
</table>

Data sources: CPS, SEC, author’s calculations

I can also examine how well the model results match what I see in the MCSUI when broken down by both race and occupation, seen in Table 8.

11Note that the desegregated equilibrium here is identical in all meaningful ways to the desegregated equilibrium induced by setting the racial bias parameter $\gamma = 0.5 \forall r$. While this would change the weights $\phi^r$, these are inconsequential once $a_j^B = a_j^W$ and $u_j^B = u_j^W \forall j$.

12I allow relative population sizes to differ in the baseline model. However, this asymmetry is not necessary to generate the patterns seen in the data–you do not need a majority/minority group dynamic. See Appendix C for a version of results where $\tau = 0.50 \forall r$ and $\gamma = 0.90 \forall r$.

13While the focus is on the observed segregated and theoretical desegregated equilibria, it’s interesting to note that there is one more segregate equilibrium supported by the model and this set of parameter values, where black workers are overemployed in $H$ occupations and white workers are overemployed in $L$ occupations. Details of this equilibrium are left to Appendix C.
and black workers rely on contacts with white workers at a higher rate for high-type jobs than the model predicts. This indicates there may be additional bias in the use of contacts by race and occupation that is not captured by the model.

Table 8: Same-race friend/family references (untargeted moments)

<table>
<thead>
<tr>
<th></th>
<th>Data</th>
<th>Model</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>White</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High</td>
<td>97.0</td>
<td>92.7</td>
<td>4.3</td>
</tr>
<tr>
<td>Low</td>
<td>86.0</td>
<td>88.9</td>
<td>-2.9</td>
</tr>
<tr>
<td>Black</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High</td>
<td>81.1</td>
<td>92.8</td>
<td>-11.7</td>
</tr>
<tr>
<td>Low</td>
<td>95.0</td>
<td>95.2</td>
<td>-0.02</td>
</tr>
</tbody>
</table>

Data source: MCSUI, author’s calculations

Overall, the model is able to capture differences in occupational choice by race. The model is able to match the targeted moments, including the percentage of black and white individuals employed in high and low occupations, the rate at which black and white individuals use referrals by occupations, as well as job finding rates and wages for high and low-type occupations. I can now measure the model’s predicted amount of employment and wage inequality due to network effects. For employment inequality, I find white workers have an employment rate 0.74 percentage points higher and for wages white workers have 1.66% higher wages, which explains about 10% of the difference in employment rates for non-college black and white workers and 14% of the difference in hourly wages for that same group. To get a better feel for the relative importance of this mechanism in explaining wage differentials, I’ve run linear regression on log hourly wages for non-college black and white workers in the CPS. When controlling for age and its square, education, gender, marital status, as well as state and year fixed effects, I am able to explain 36% of the observed hourly
wage differential for this group. Finally adding occupation (using 4 digit codes) and industry controls I am able to explain 62% of the gap.

The differences in employment rates are due to black workers selecting into an occupation with a higher separation rate. Table 9 displays employment rates by race and occupation in both the segregated and desegregated steady states. Figure 9 displays the wage profiles of black and white workers in the segregated equilibrium, as well as their (identical) wage profiles in the desegregated equilibrium. Figure 9 also displays the productivity of each ability \( x \) worker if they were employed in \( H \) or \( L \) occupation types, as well as vertical lines at \( x^*_r \) in the segregated equilibrium, labeled as 'black' and 'white', and the desegregated equilibrium (where \( x^*_r \) is the same for both black and white workers).

Table 9: Employment Rates

<table>
<thead>
<tr>
<th></th>
<th>Segregated</th>
<th>Desegregated</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Black</td>
<td>White</td>
</tr>
<tr>
<td>Overall</td>
<td>70.1</td>
<td>70.9</td>
</tr>
<tr>
<td>High</td>
<td>69.94</td>
<td>73.04</td>
</tr>
<tr>
<td>Low</td>
<td>70.24</td>
<td>68.98</td>
</tr>
</tbody>
</table>

Because there are asymmetries in the exogenous parameters used to describe the high and low occupation types (including the cost of opening a vacancy, the matching technologies, and the flow utility of unemployment), we do not see workers sort perfectly into their most productive match even in the desegregated equilibrium. This has important consequences for who gains and who loses when switching from the segregated to desegregated equilibrium. The segregated equilibrium pushes white workers into more productive roles by
making it less costly for them to obtain those roles, while for black workers it’s the opposite—they’re pushed into less productive roles. When moving to the desegregated equilibrium, white workers lose this advantage and black workers no longer have the same incentive to work in less productive occupations. Thus the desegregated equilibrium is beneficial for black workers, but harmful for white workers.
So far I have assumed $\alpha = 0$. How do the calibration results differ if the true value of $\alpha$ is some positive number? Recalibrating the model to allow for $\alpha > 0$ generates larger wage differentials between black and white workers. This can be interpreted through the wage equation, where workers are directly
compensated for the value of their networks to the firm. As $\alpha$ increases, firms receive a greater share of the value of an expansion. Since white workers have substantially better networks than black workers in the high-type occupations, they receive a greater boost to their wages. In this sense, 1.66% can be viewed as a lower bound for the wage differentials generated by this model. Figure 10 shows the model-generated wage differentials when recalibrated for different values of $\alpha$.

Figure 10: Percent difference in black-white wages with $\alpha \in [0, 1]$
3.8 Efficiency, Stability, and Policy

I define social welfare $W$ as aggregate output plus the flow value of unemployment net of vacancy creation costs.

$$W = \sum_r \tau^r \int_{x_j} e_H^r A_H x dx + \sum_r \tau^r a_L^r e_L^r A_L + \sum_r \sum_j z_j (\tau^r a_j^r u_j^r) - \sum_j v_j c_j$$

In a scenario with occupational segregation, some workers are sacrificing their productive advantage for the benefit of an increased likelihood of finding a job. This trade-off exists at the worker level and can also exist in the aggregate. Figure 11 shows the change in aggregate welfare when moving from the segregated to the desegregated equilibrium. It also shows the change separately for black and white workers, excluding any analysis of vacancy costs.

The results indicate that referral networks can create inequality while simultaneously enhancing aggregate welfare\(^1\). In the case here, referrals help the majority group (white workers) and harm the minority group (black workers). In aggregate, the gains for the majority group outweigh the losses for the minority group and lead to a measure of higher aggregate welfare in the segregated steady state relative to the desegregated steady state, although the difference is quite small.

The fall in productivity from the segregated to desegregated steady state is due in part to less employment among white workers in the high-type occupancy.\(^2\)

\(^1\)Galenianos (2021) uses a referral model to examine inequality as well as overall welfare. The effects of referrals on welfare are subtle. In this paper, referrals reduce welfare when workers face a different probability of forming a match despite having the same productivity. However, when worker heterogeneity is due to productivity differences, the network favors the more productive type and enhances welfare despite increasing inequality.
pation. While more black workers are employed in the high-type occupation, increasing productivity for the black population, their minority status makes their gains relatively small in the aggregate. Beyond this, vacancy costs are higher, as well as the value of unemployment flows, because it is harder to form a match through the referral networks in the desegregated steady state. This is a direct consequence of the convex network effects captured by $\Gamma_j$, which generates increasing returns to the proportion of your network employed in the occupation you’re searching in. Integration diminishes individuals’ employment prospects due to weaker network effects when there is a more even mix of occupations within an individuals’ network.
Social inequalities demand policies addressing information gaps, network divisions, and leveraging feedback effects and social multipliers. While efforts to reduce homophily could be effective in reducing informational disadvantages for certain groups, it may not be necessary. The model’s results show...
that once these groups are evenly distributed across occupations, a desegregated equilibrium is supported even in a world with substantial homophily.

However, when multiple equilibria exist, questions will arise about their stability. Dynamic processes select among equilibria, and it is informative to ask how we came to select a particular equilibrium, and how stability matters for the effectiveness of policies. In this model, we are in equilibrium when no worker can get higher utility from moving to another occupation. This decision is captured by the proportion of workers searching and working in each occupation\(^{15,16}\). The idea of stability is to examine the robustness of a set of equilibria to perturbations in the underlying game.

Define \( \Delta U^r(x, a^W_H, a^B_H) = U^r_H(x) - U^r_L \) (note that \( U^r_j \) are a function of \( a^r_j \) through the matching function, which has been excluded from the notation thus far to reduce clutter). At \( x^*_r \), in steady state \((\hat{a}^W_H, \hat{a}^B_H)\), we have \( \Delta U^r(x^*_r, \hat{a}^W_H, \hat{a}^B_H) = 0 \). I will define the stability concept using a standard myopic adjustment process of strategies\(^{17}\). Myopic adjustment dynamics have the property that at each instant the direction of movement in each population’s strategy is weakly payoff increasing, given the current behavior of the other population(s)\(^{18}\). Myopic adjustment simply requires that utility increase along the adjustment path (holding fixed the play of other players).

In the case of isolated equilibria, the Jacobian matrix informs us about

\(^{15}\)denoted by \( a^r_j \), with \( a^r_H + a^r_L = 1 \) \( \forall r \) and \( a^r_H = \int_{x \geq x^*_j} g(x)dx \) \( \forall r \).

\(^{16}\)This is an equilibrium of pure strategies, where \( a^r_j \) is the measure of players in group \( r \) choosing pure strategy \( j \).

\(^{17}\)This is similar to Buhai and Leij (2023).

\(^{18}\)See Swinkels (1992) for further discussion of myopic adjustment strategies.
their stability\textsuperscript{19}. Examining both the selected segregated equilibrium and the hypothetical desegregated equilibrium, I find that both are hyperbolic, while the segregated is a sink (therefore stable) and the desegregated equilibrium is a saddle (therefore not stable)\textsuperscript{20}. This is relevant when it comes to policy recommendations, indicating that policies with the goal of moving to and maintaining the desegregated equilibrium would need to be permanently maintained, otherwise society will naturally move to a segregated equilibrium. There is some empirical support for this in Kurtulus (2013), who uses Affirmative Actions bans at the state level to examine the impact of eliminating Affirmative Action policies on employment. She finds that there are deleterious effects on employment for minorities once the bans are set in place, indicating a lack of persistence in Affirmative Action policies. Myers (2007) focuses specifically on the Affirmative Action ban in California in 1996, and finds that employment among women and minorities dropped sharply, suggesting again a lack of persistence in Affirmative Action policies.

\textsuperscript{19}Consider a dynamic system guided by the differential equation $\dot{a}_r^H = k\Delta U^r(x^*_r, a^W_r, a^B_r)$. This is essentially defining the players response function. The player, defined by their ability and race, chooses their action (which occupation to search in) to maximize the expected payoff given their assessment of other players actions. Define the Jacobian, evaluated in the steady state, as

$$
J[\Delta U^r(x)] = 
\begin{bmatrix}
\frac{\partial \Delta U^B(x^*_H, a^W_H, a^B_H)}{\partial a^H_B} & \frac{\partial \Delta U^B(x^*_H, a^W_H, a^B_H)}{\partial a^W_H} & \frac{\partial \Delta U^B(x^*_H, a^W_H, a^B_H)}{\partial a^B_H} \\
\frac{\partial \Delta U^W(x^*_W, a^W_H, a^B_H)}{\partial a^W_W} & \frac{\partial \Delta U^W(x^*_W, a^W_H, a^B_H)}{\partial a^W_H} & \frac{\partial \Delta U^W(x^*_W, a^W_H, a^B_H)}{\partial a^B_H}
\end{bmatrix}
$$

A steady state is hyperbolic if the Jacobian has no eigenvalues with zero real parts. If the steady state is hyperbolic and the eigenvalues all have negative real parts, the steady state is called a sink. If the eigenvalues all have positive real parts, it’s called a source. Otherwise, a hyperbolic steady state is called a saddle. A sink is asymptotically stable. For a review of this material, see Fudenberg and Levine (1998).

\textsuperscript{20}The third (segregated) equilibrium discussed in Appendix C is a saddle, therefore also unstable.
3.9 Conclusion

I have proposed a search and match model where social interactions are an important component of the matching process. I have incorporated worker heterogeneity in ability and network composition, and allowed for minority and majority groups. This model is able to rationalize salient features of the data, including differences in the use of referral networks by race and differences in occupational choice by race. I find that racial homophily, or social segregation, can perpetuate occupational segregation in the steady state and give rise to inter-group inequality that aligns with empirically observed racial disparities. In particular, this mechanism alone can generate a 1.66% difference in wages and a 0.74 percentage point difference in employment, respectively accounting for 14 percent and 10 percent of the observed gaps for black and white non-college workers.

I also examine the welfare effects of a segregated versus a desegregated equilibrium under the same fundamentals, and find that aggregate welfare is higher in the segregated steady state. However, these gains accrue to white workers. Beyond this, I find that while a desegregated equilibrium is supported by the model, it is unstable. This has implications for the long-term impact of policies such as affirmative action. Once these policies are removed, society would likely move back towards a segregated equilibrium.

Future theoretical work could also include endogenous on-the-job network formation to study the importance of business contacts, in particular for college-educated workers, as well as on-the-job search. Solving for a fully dy-
namic model would also allow for analysis of transition dynamics.

3.10 Appendix

3.10.1 Appendix B

**Proposition 4.1.** The referral component of the job finding rate \( p^r_j \) is decreasing in unemployment \( u^r_j \) and \( u^r\_¬_j \) \( \forall j, r \), therefore increasing in employment, i.e. \( \frac{\partial p^r_j}{\partial e^r_j} > 0 \) and \( \frac{\partial p^r_j}{\partial e^r\_¬_j} > 0 \) \( \forall j, r \). Assuming \( \Gamma_j \) is not too large, the referral job filling rate \( k^r_j \) is increasing in unemployment \( u^r_j \) and \( u^r\_¬_j \) \( \forall j, r \), therefore decreasing in employment, i.e. \( \frac{\partial k^r_j}{\partial e^r_j} < 0 \) and \( \frac{\partial k^r_j}{\partial e^r\_¬_j} < 0 \) \( \forall j, r \).

**Proof.** We have

\[
 p^r_j = \kappa_j (e^r_j)^\Gamma_j = \kappa_j (\phi^r a^r_j e^r_j + (1 - \phi^r) a^r\_¬_j e^r\_¬_j)^\Gamma_j
\]

so that

\[
 \frac{\partial p^r_j}{\partial e^r_j} = \Gamma_j \kappa_j \phi^r a^r_j (e^r\_¬_j a^r\_¬_j (1 - \phi^r) + e^r_j a^r_j \phi^r)^{\Gamma_j - 1} > 0
\]

\[
 \frac{\partial p^r_j}{\partial e^r\_¬_j} = \Gamma_j \kappa_j (1 - \phi^r) a^r\_¬_j (e^r\_¬_j a^r\_¬_j (1 - \phi^r) + e^r_j a^r_j \phi^r)^{\Gamma_j - 1} > 0
\]

Now consider

\[
 k^r_j = \frac{u^r_j (e^r_j)^\Gamma_j}{a^r_j e^r_j + a^{-r} e^r_j} = \frac{(1 - e^r_j)(\phi^r a^r_j e^r_j + (1 - \phi^r) a^{-r} e^r_j)^{\Gamma_j}}{a^r_j e^r_j + a^{-r} e^r_j}
\]
\[
\frac{\partial k_j^r}{\partial e_j^r} = -\left( \frac{\tilde{e}_j^r(1 - \phi^r)a_j^- + e_j^r \phi^r a_j^r}{(e_j^r a_j^- + e_j^r a_j^r)^2} \right)
\]

\[
* \left( \frac{(e_j^r)^2(a_j^-)^2(1 - \phi^r)}{2} \right) \]

\[
+ e_j^r a_j^- (1 - (1 - e_j^r)(1 + \Gamma_j)\phi^r) + e_j^r \phi^r (a_j^r)^2(1 - (1 - e_j^r)\Gamma_j) \right) < 0
\]

In order for the final line to have a positive value and guarantee that the partial derivative is negative, we need \((1 - e_j^r)\Gamma_j < 1\) and \((1 - e_j^r)(1 + \Gamma_j)\phi^r < 1\), i.e. \(\Gamma_j\) cannot be too large.

**Proposition 4.2.** The aggregate matching function exhibits decreasing returns to scale.

**Proof.** Here I multiply \(u_j^r\ \forall r\) and the occupation-specific vacancy rate \(v_j\) by a factor \(\omega > 1\). Then

\[
\theta_j(\omega v_j)^\eta(\omega u_j)(1-\eta) + \omega u_j^r \kappa_j (\phi^r a_j^r (1 - \omega u_j^r)^2 (1 - \omega u_j^-))^{F_j}
\]

\[
= \omega M_j + \omega u_j^r \kappa_j (\phi^r a_j^r (1 - \omega u_j^r) + (1 - \phi^r) a_j^- (1 - \omega u_j^-))^{F_j}
\]

\[
= \omega M_j + \omega u_j^r \kappa_j (\phi^r a_j^r (1 - \phi^r) a_j^- - \omega \bar{u}_j^r)^{F_j}
\]

\[
= \omega M_j + \omega P_j \left( \frac{\phi^r a_j^r + (1 - \phi^r) a_j^-}{\bar{e}_j^r} \right)^{F_j}
\]
It is necessarily the case that $\phi^r a_j^r + (1 - \phi^r)a_j^{-r} - \omega \bar{u}_j^r < \bar{e}_j^r$. Written differently:

$$\phi^r a_j^r + (1 - \phi^r)a_j^{-r} - \omega \bar{u}_j^r < \phi^r a_j^r + (1 - \phi^r)a_j^{-r} - \bar{u}_j^r$$

$$\omega \bar{u}_j^r > \bar{u}_j^r$$

$$\omega > 1$$

Since $\left(\frac{\phi^r a_j^r + (1 - \phi^r)a_j^{-r} - \omega \bar{u}_j^r}{\bar{e}_j^r}\right)^\Gamma_j < 1$, the function exhibits decreasing returns to scale.

### 3.10.2 Appendix C

**Equal population sizes:** I allow relative population sizes to differ in the baseline model. However, I do not need a majority/minority group dynamic to generate the patterns seen in the data. Here I show a version of the results where $\tau^r = 0.50$ and $\gamma^r = 0.90 \forall r$. I will maintain the same set of targeted moments in this hypothetical world of equal population sizes, seen in Table 11.

Table 10: Parameter values: equal population sizes

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$A_H, A_L$</td>
<td>0.727, 1.324</td>
</tr>
<tr>
<td>$z_H, z_L$</td>
<td>-0.049, -0.018</td>
</tr>
<tr>
<td>$\theta_H, \theta_L$</td>
<td>0.041, 0.041</td>
</tr>
<tr>
<td>$\kappa_H, \kappa_L$</td>
<td>0.537, 0.110</td>
</tr>
<tr>
<td>$\Gamma_H, \Gamma_L$</td>
<td>2.579, 1.249</td>
</tr>
<tr>
<td>$\sigma_x$</td>
<td>0.420</td>
</tr>
</tbody>
</table>
Table 11: Model Fit and Desegregated Equilibrium: equal population sizes

<table>
<thead>
<tr>
<th></th>
<th>Data</th>
<th>Targeted</th>
<th>Segregated</th>
<th>Desegregated</th>
</tr>
</thead>
<tbody>
<tr>
<td>% B employed in $H$</td>
<td>37%</td>
<td>Y</td>
<td>37%</td>
<td>45%</td>
</tr>
<tr>
<td>% W employed in $H$</td>
<td>48%</td>
<td>Y</td>
<td>48%</td>
<td>45%</td>
</tr>
<tr>
<td>job-finding rate (B)</td>
<td>0.10</td>
<td>Y</td>
<td>0.10</td>
<td>.0998</td>
</tr>
<tr>
<td>job-finding rate (W)</td>
<td>0.10</td>
<td>Y</td>
<td>0.10</td>
<td>.0998</td>
</tr>
<tr>
<td>mean wages (H)</td>
<td>1.39</td>
<td>Y</td>
<td>1.39</td>
<td>1.395</td>
</tr>
<tr>
<td>90th percentile wages (H)</td>
<td>2.22</td>
<td>Y</td>
<td>2.22</td>
<td>2.26</td>
</tr>
<tr>
<td>mean wages (L)</td>
<td>1.00</td>
<td>Y</td>
<td>1.00</td>
<td>1.001</td>
</tr>
</tbody>
</table>

% jobs from network:
- Black (L): 35% Y 35% 32%
- Black (H): 22% Y 22% 30%
- White (L): 32% Y 32% 32%
- White (H): 33% Y 33% 30%

Data sources: CPS, SEC, author’s calculations
Figure 12: Wages and Productivity: equal population sizes
In contrast to the results where the population sizes differ by race, both black and white workers move to more suitable occupations in the desegregated equilibrium. Also unlike the previous results, in the aggregate the gains to black workers cancel out the losses to white workers when moving from the segregated
to the desegregated equilibrium. However, once vacancy costs are accounted for aggregate welfare still decreases. It is more difficult to match workers and firms together when they worker’s networks contain fewer contacts in the same occupation as them, which is the case in the desegregated equilibrium. Put differently, the positive network externality generated by searching in the same occupation as your peers dominates the negative externality generated by the misallocation of ability levels for black workers in the segregated equilibrium.

**The (other) segregated equilibrium:** While the focus is on the observed segregated and theoretical desegregated equilibria, it’s interesting to note that there is one more segregate equilibrium supported by the model and the main set of parameter values, where black workers are overemployed in H occupations and white workers are overemployed in L occupations. Results for this equilibrium are available in Table 12 and, for convenience, the results for the desegregated equilibrium are reported again as well. For employment and wage differences, black workers have an employment rate 16 percentage points higher than white workers, and a wage rate that is 9% higher on average. Note also that this equilibrium is a source (and therefore unstable).
Table 12: Three equilibria

<table>
<thead>
<tr>
<th></th>
<th>Data</th>
<th>Desegregated</th>
<th>Segregated (other)</th>
</tr>
</thead>
<tbody>
<tr>
<td>% B employed in H</td>
<td>37%</td>
<td>45%</td>
<td>87%</td>
</tr>
<tr>
<td>% W employed in H</td>
<td>48%</td>
<td>45%</td>
<td>32%</td>
</tr>
<tr>
<td>job-finding rate (B)</td>
<td>0.10</td>
<td>.0998</td>
<td>.34</td>
</tr>
<tr>
<td>job-finding rate (W)</td>
<td>0.10</td>
<td>.0998</td>
<td>.098</td>
</tr>
<tr>
<td>mean wages (H)</td>
<td>1.39</td>
<td>1.395</td>
<td>1.42</td>
</tr>
<tr>
<td>90th percentile wages (H)</td>
<td>2.22</td>
<td>2.26</td>
<td>1.96</td>
</tr>
<tr>
<td>mean wages (L)</td>
<td>1.00</td>
<td>1.001</td>
<td>1.07</td>
</tr>
<tr>
<td>% jobs from network: Black (L)</td>
<td>35%</td>
<td>32%</td>
<td>3%</td>
</tr>
<tr>
<td>Black (H)</td>
<td>22%</td>
<td>30%</td>
<td>85%</td>
</tr>
<tr>
<td>White (L)</td>
<td>32%</td>
<td>32%</td>
<td>34%</td>
</tr>
<tr>
<td>White (H)</td>
<td>33%</td>
<td>30%</td>
<td>22%</td>
</tr>
</tbody>
</table>

Data sources: CPS, SEC, author’s calculations

3.11 Bibliography


4 Chapter 3: Returns to Experience and Hours Worked: Racial Disparities in the United States

4.1 Abstract

The forces driving differences in the supply of labor between black and white workers over the past few decades are only partially understood. In this paper, I use individual fixed effects combined with an instrumental variables approach to document the extent to which returns to work experience differ for black and white workers. I then use a life-cycle model with a learning-by-doing human capital production function to assess the consequences of these differences for the supply of labor. Returns to an extra thousand hours of work experience for the typical white worker are 23 cents per hour in 2012 USD (amounting to an additional $478 per year of full time work), compared to 12 cents for an otherwise identical black worker (amounting to an additional $250 per year). Using a life-cycle model, differences in returns to experience combined with simulated differences in choices of hours worked can account for approximately 10 percent of the measured difference in average wages over the life-cycle between black and white workers. The racial gap in returns to work experience both directly affects lifetime earnings, and indirectly affects lifetime earnings through induced differences in labor supply choices. The model shows that different choices in hours worked explains approximately 18 percent of the generated differences in lifetime earnings, while the remaining 82 percentage is explained directly by
differences in returns to experience.

4.2 Introduction

In this paper I will focus on the differences in returns to experience between male black and white workers and its effect on hours worked over the life-cycle. Results suggest that at least some of the differences in black men’s supply of labor are responses to low returns to extra years of work experience. This analysis allows me to account for the direct effects of lower returns to experience on inequality as well as the indirect effect through decreased hours of work.

I use the Panel Study of Income Dynamics (PSID) to estimate a life-cycle model with a learning-by-doing human capital production function. In the first stage, a wage equation is estimated to determine how wages grow with work experience, where that growth is allowed to differ by race. In the second stage, the wage equation parameters are treated as known and the preferences parameters are estimated using generalized method of moments (GMM). For the wage equation, I include person fixed effects to control for an individuals’ innate market productivity, while I allow gains in human capital accumulation with a direct measure of work experience. Including person level fixed effects is crucial since I would expect innate ability and work experience to be positively correlated if high ability workers specialize more in market production, and spend less time on leisure. I also use instrumental variables to address additional issues that tend to plague observation studies, including reverse causality (for example, your wages will affect choices about hours worked, and thus the amount of experience you accumulate), time-varying unobserved heterogeneity (for exam-
ple, a health shock could effect hours worked and an individuals wages), and measurement error (concerns about measurement error around hours worked are well known, and will bias estimates of my parameter of interest towards zero). The instrument I use is age, which is strongly correlated with hours of work experience, and it is reasonable to assume satisfies the exclusion restriction. In other words, I would expect it is not correlated with the error term, meaning it is not correlated with any component of wages once experience is taken into account and there are no omitted variables in the model through which age effects wages. I would expect age to affect wages only through the amount of accumulated work experience.

I then use these results to quantitatively assess the consequences of lower returns to experience for black workers on hours of work over the life cycle. I parameterize the preference parameters using data for white workers and then ask how the model’s predictions change when setting just the returns to experience to the values observed for black workers.

I start by documenting the extent to which the experience premium differs for black and white workers, and examine whether these differences change over time using the CPS. I find a persistent gap since the 1990s, with returns to an extra thousand hours of work experience for the typical white worker of 23 cents per hour in 2012 USD (amounting to an additional $478 per year of full time work), compared to 12 cents for an otherwise identical black worker (amounting to an additional $250 per year). One consequence of this difference is that a reduction in hours worked for black workers is less costly than it is for white workers. When this cost is lower, we would expect workers to reduce
their market hours. I use a life-cycle model with human capital accumulation to assess the consequences of lower returns to experience for black men on their supply of labor relative to white men. Time is allocated between work and leisure. I parameterize the model using data for white workers, then ask how the model’s predictions change when returns to experience are set to the values observed for black workers. I find that differences in returns to experience combined with simulated differences in choices of hours worked can account for approximately 10 percent of the measured difference in average wages over the life-cycle between black and white workers.

4.2.1 Literature

A substantial body of literature in labor economics has examined differences in various labor market outcomes across racial groups. This research tends to restrict its focus to only two groups at a time, and usually investigates earnings gaps. For an earlier review of the literature, refer to Altonji and Blank (1999), where Section 6 in particular discusses the impact of differences in returns to experience for black and white workers. Fairlie and Sundstrom (1999) is another earlier study focusing in particular on the unemployment gap between black and white workers. More recent reviews include Fryer (2011), and Lang and Lehmann (2012). Fryer (2011) focuses on the significance of discrimination, and in particular its declining significance in explaining racial inequality. The current study does not take a stance on the cause or causes of differences in returns to work experience, in particular the role of discrimination, but does allow for differences in hours worked to reflect a rational choice by black workers.
to supply less labor in response. Bayer and Charles (2018) examine black-white earnings differences since the 1940s, noting that the gap narrows until the 1970s, and has now grown as wide as it was in the 1950s. Chetty, Hendren, and Jones (2020) take an inter-generational perspective, finding that after conditioning on parent income, the black-white male income gap is driven by differences in wages and employment rates.

Differences in hours worked between black and white workers is a known issue. Bell (1998) notes that “black males work 20 percent fewer annual hours than white males”. Bell finds that black and white workers display different preferences for work, and argues that these differences in work preferences between black and white workers should not exist if they place equal value on an extra hour of work. Her empirical estimates suggest that black and white workers do place the same value on an extra dollar of wages and income. More recently, Ritter and Taylor (2011) focus on difference in unemployment and posits that statistical discrimination could play an important role. Finally, a recent paper by Rauh and Valladares-Esteban (2023) is most similar in scope, examining measured differences in the ability to accumulate human capital over the life-cycle between black and white workers as an explanation for how wages diverge as workers age. They find that pre-market differences (i.e. differences in initial levels of capital and differences in the ability to accumulate capital) are crucial for explaining racial gaps in earnings. They also find that labor supply differences are quantitatively important for explaining earnings gaps.

Many studies have worked to incorporate human capital in the life-cycle labor supply model. Some earlier studies include MaCurdy (1983), Hotz,
Kydland and Sedlacek (1988), and Shaw (1989). A more recent paper by Keane (2016) discusses the importance of including human capital in the life-cycle labor supply model, with a focus on the size of labor supply elasticities and implications for tax policy.

The analysis done here is similar to papers analyzing labor supply decisions by gender, instead of race. These include Caucutt, Guner, and Knowles (2002), Olivetti (2006), and Attanasio, Low, and Sanchez-Marcos (2008). Olivetti (2006), for example, uses a four-period model where she estimates returns to experience and uses these estimates to show the effect that increases in the returns to experience have on hours worked by women over time. In a similar vein, Erosa, Fuster and Restuccia (2016) examine how much of the gender wage gap over the life cycle is due to the fact that working hours are lower for women than for men. They assume there are no differences by gender in the human capital technology. Knowles (2007) focuses on the importance of heterogeneity in returns to experience across occupations to understand female labor supply decisions. Azmat, Guell, and Manning (2006) focus in particular on gender gaps in unemployment. The literature on the labor supply of women tends to focus on fertility and household production decisions, which this paper abstracts from while focusing on the labor supply of black and white men.

4.3 Empirical Motivation

I use two data sources to evaluate returns to work experience by race. The Current Population Survey (CPS), including the Annual Social and Economic Supplement (ASEC), and the Panel Study of Income Dynamics (PSID). The full
life-cycle model will rely entirely on the PSID. The CPS is used to further verify
the main mechanism of the paper: differences in returns to experience by race.

The CPS is the source of official US government statistics on employ-
ment and unemployment, and is designed to be representative of the civilian
non-institutional population. The Annual Social and Economic Supplement
(ASEC) applies to the sample surveyed in March, and extends the set of de-
mographic and labor force questions asked in all months to include detailed
questions on income. There is not direct measure of labor market experience,
and instead I must rely on ‘potential’ experience using age and education. Labor
force and income information correspond to the previous year.

The PSID is a longitudinal study of a sample of US individuals (men,
women, and children) and is the longest-running representative household panel
for the United States. Survey waves are annual from 1968 to 1997, and biennial
since then. The PSID has some advantages over the CPS: since it is a panel
data set, I am able to incorporate person-level fixed effects. It also allows for a
more direct calculation of work experience, instead of using years of potential
work experience. And finally it has the consumption and hours data needed to
estimate the Euler equation.

I consider only men between the ages of 20 and 60. I drop records if 1)
there is no information on age, income, occupation, or hours of work, 2) they
earn real hourly wages outside the 1st and 99th percentile. For estimation of
the Euler equation, I also drop the years 1988 and 1989, which do not have food
consumption data, and exclude individuals whose consumption lies outside of
the 5th and 95th percentile, and only use individuals who are in the sample for three subsequent periods, due to the first-differencing in the Euler equation.

4.3.1 Hours worked

I begin the descriptive analysis with information about the labor supply of black and white workers, then show wage profiles. Table 13 documents the differences in male black and white work hours in the U.S.

Table 13: Work Patterns: Black and Whites, CPS ASEC (1990-2021)

<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>White</th>
<th>Black</th>
<th>% Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Hours per Week</td>
<td>37.7</td>
<td>31.1</td>
<td>19.2</td>
<td></td>
</tr>
<tr>
<td>Average Weeks per Year</td>
<td>42.6</td>
<td>35.6</td>
<td>17.7</td>
<td></td>
</tr>
<tr>
<td>Average Annual Hours</td>
<td>1832.3</td>
<td>1460.9</td>
<td>22.6</td>
<td></td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Greater than 0 weeks of work</th>
<th>All</th>
<th>White</th>
<th>Black</th>
<th>% Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Hours per Week</td>
<td>42.7</td>
<td>31.1</td>
<td>19.2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average Weeks per Year</td>
<td>48.0</td>
<td>35.6</td>
<td>17.7</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average Annual Hours</td>
<td>2072.6</td>
<td>1460.9</td>
<td>22.6</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 1 indicates that the majority of differences in average annual hours is due to black workers selecting out of the labor force entirely or being unable to get matched to a position. While these averages are informative, I am also interested in life-cycle profiles of hours worked. It’s well-known that examining cohorts (defined by date of birth) through successive surveys allows for better disentanglement of generational versus life-cycle components than simply looking at aggregates.
I estimate the following regression:

\[ \ln h_{it} = \alpha^h_0 + \alpha^h_1 A_{it} \times C_{it} \times R_i + \tilde{Y}_t + \epsilon^h_{it} \]

where \( A_{it} \) represents age dummies, \( C_{it} \) cohort dummies, \( R_i \) a race dummy, and \( \tilde{Y}_t \) are transformed year dummies. Here I calculate an interaction between age, cohort, and race dummies to allow for the shape of the age profiles to change across cohorts and races. The year dummies are transformed so that they are orthogonal to a time trend:

\[ \tilde{Y}_t = Y_t - [(t - 1)Y_2 - (t - 2)Y_1] \]

where \( Y_t \) is the usual time dummy. In this case any growth will be attributed to age and cohort effects, while the transformed year effect will capture only cyclical fluctuations that average to zero. Figure 14 displays the results for annual hours using cohorts defined by their birth year over ten year periods and, to make patterns across cohorts more easily identifiable, for cohorts defined over larger periods of time. Figure 15 displays the same analysis for individuals with greater than zero weeks of work.
Figure 14: Life-cycle Hours (CPS)
There is a life-cycle profile to hours across cohorts and races. Hours increase from ages 20-30 and then, for those who continue to work at all, stay approximately the same. White workers see a decrease across cohorts in hours worked throughout the life-cycle, although this pattern disappears when focusing on those who work at all. The gap between black and white workers hours over the life-cycle is obvious in Figure 14 and still visible in Figure 15. The differences in hours worked between black and white workers has been relatively persistent across cohorts.
4.3.2 Wages and the Experience Premium

Decisions about optimal work hours within a life-cycle framework are influenced by factors beyond current wage rates. Dynamic aspects, such as the returns to experience, are also important determinants. For this reason, we want to examine wages over the life-cycle as well. The same strategy is used here as was used for hours worked. In particular, I run the following regression

\[ \ln w_{it} = \alpha_{0}^{w} + \alpha_{1}^{w} A_{it} \times C_{it} \times R_{i} + \bar{Y}_{t} + \epsilon_{it}^{w} \]

Figure 16 depicts \( \alpha_{0}^{w} + \alpha_{1}^{w} \) for each cohort and race. Note that because of selection issues these figures do not necessarily reflect the average offer wage, which is the one relevant for labor supply decisions.
There is a pronounced life-cycle profile to earnings across cohorts and races. As expected, earnings grow more rapidly in the early portion of a person’s life-cycle, generally leveling off later in life. Shifts up or down in wage profiles across cohorts are not particularly obvious. For white workers, it’s possible that there has been a small downward shift. While black workers do start at a slightly lower wage than white workers, on average, what is even more pronounced is the lack of growth over the life cycle relative to white workers. In Figure 17, we can see how the difference in wages between black and white workers evolves over the life-cycle. The wage gap widens as they age, in particular during the initial 10 years of work when wage growth is highest, reflecting the steeper wage
profile white workers face in the early part of their career.

Figure 17: Life-cycle Earnings Differences (White - Black)

In order to calculate returns to experience, measured in increases in real wages, I assume that a worker's general experience can raise their labor income. I measure experience in the CPS as 'potential' years of experience since age 18, specifically the person's age minus their education beyond highschool minus 18. I first estimate time-varying returns to work experience to assess whether the difference between black and white workers has varied meaningfully over time. I estimate a wage equation by including the total number of years of full-time work experience (and its square). To allow the estimated returns to experience to vary across years, I interact a worker's full-time job experience with period dummies that capture 5-year intervals, i.e. $\tau \in \{1985 - 1989, 1990 - 1994, 1995 - 1999, 2000 - 2004, 2005 - 2009, 2010 - 2014, 2015 - 2019\}$. I would
expect a higher coefficient on the interaction for periods in which experience are more important to production. The following regression is run for the years 1985-2020, with the coefficients allowed to vary at 5-year intervals.

\[
\log w_{it} = \alpha + \beta_{\text{Exp}R} \text{Race}_i \text{Exp}_{it} + \beta_{\text{Exp}^2R} \text{Exp}^2_{it} \text{Race}_i \\
+ \beta_X [\text{Year}_t, \text{Cohort}_i, \text{Race}_i, \text{Industry}_{it}, \text{Educ}_{it}, \text{Marst}_{it}]
\]

Why include cohort fixed effects? Cohort data can be used to control for unobservable fixed effects just as with panel data. Results are nearly identical if occupational FE are also included.

I use the estimated coefficients on Exp and their squared terms to construct year-specific returns to experience.

\[
Year_{\text{Exp}}^T = \hat{\beta}_{\text{Exp}}^T * T + \hat{\beta}_{\text{Exp}^2}^T * T^2
\]

\(Year_{\text{Exp}}^T\) gives the predicted returns to \(T\) years of general work experience. As a baseline, I choose \(T = 1\). In Figure 4 periods are labeled using the first year in that interval:
One extra year of experience is associated with somewhere between 3.3% and 3.8% higher wages for white workers throughout this time period. For black workers, these returns fall between 2.83% and 3.14% over this time period. There has been no significant change in relative returns to experience between black and white workers since the 1990s, which could contribute to persistent between-group differences in hours worked. See Table 14 for a complete set of results.
Table 14: Returns to Experience over time

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<tr>
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<th>Coeff</th>
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4.4 Model

4.4.1 Overview of Strategy

In this paper I will estimate a life-cycle labor supply model where workers make joint decisions about savings and human capital investment, incorporating uncertainty about future wages and hours. With human capital accumulation, the price of time is no longer just the wage—it is the wage plus returns to work experience. This results in labor supply elasticities that are a functions of preference and also wage process parameters. It is these wage process parameters that I allow to differ by race. Beyond this, labor supply elasticities become functions of age, with younger workers experiencing reduced elasticities and older workers being far more responsive to wages.

The estimation is done in two stages. In the first stage, a wage equation is estimated to determine how wages grow with work experience, similar to the empirical analysis used as motivation. In the second stage, the wage equation parameters are treated as known and the preference parameters are estimated using generalized method of moments (GMM). Valid instruments used in GMM are known by workers at time \( t \), so they are uncorrelated with the forecast error at time \( t + 1 \).

This paper utilizes PSID’s panel data structure to estimate the structural parameters of the life-cycle labor supply model. I allow for uncertainty among agents about future realizations of exogenous variables. Beyond this, I incorporate human capital accumulation through learning-by-doing and thus endogenous determination of wages. I then use these results to quantitatively
assess the consequences of lower returns to experience on hours of work over the life cycle. I parameterize the model using data for white workers and then ask how the model’s predictions change when setting the parameters governing returns to experience to the values observed for black workers. Note that reduced returns to experience is different from a level change in wages. Lower wages should cause individuals of all ages to work less, while a reduction in the returns to work experience makes reduced work hours early in the life cycle relatively less costly and thus affects individuals of different ages in different ways.

4.4.2 Model Details

The individual worker chooses hours of work $N_t$ and consumption $C_t$ to maximize the present discounted value of uncertain and time-separable utility defined over leisure $L_t$ and consumption, $U(L_t, C_t)$.

$$V(A_t, K_t, R_t) = \max_{N_t, C_t} U(L_t, C_t) + \beta E_t V(A_{t+1}, K_{t+1}, R_{t+1})$$ (1)

where $V(A_t, K_t, R_t)$ is the value function determined by the stock of assets $A_t$, human capital $K_t$, and the market price for services from a unit of human capital $R_t$. Allow $\beta$ to be the discount factor, $N_t + L_t = 1$, and $E_t$ is the expectations operator reflecting uncertainty about future earnings.

The asset accumulation restraint is given by

$$A_{t+1} = (1 + r_t)(A_t + w_t N_t - C_t)$$ (2)
where income comes from both interest earnings \( r_t A_t \) and labor earnings \( w_t N_t \). Assume the consumption good is acting as the numeraire.

Following, for example, Shaw (1989) and Hokayem and Ziliak (2014), the observed wage rate \( w_t \) is specified as the product of human capital stock and the unobserved rental rate on human capital, \( R_t \), so that

\[
w_t = R_t K_t
\]

\( R_t \) is the market price for services from a unit of human capital at time \( t \). Human capital, the primary object of interest in this paper, is the stock of skills that the labor force possesses, which will be measured by work experience. Wage rates are endogenous to the agents consumption and labor supply decisions as a result of agents ability to increase their future wages by choosing their hours of work this period, wage rates are endogenous to the agents consumption-leisure decisions.

I’ll specify current human capital in a manner analogous to Gemici and Wiswall (2014) specification for skill production, where

\[
K_{it} = \exp \left( \beta_1 \sum_{k=1}^{t-1} N_{ik} + \beta_2 \left( \sum_{k=1}^{t-1} N_{ik} \right)^2 + \alpha_i + \epsilon_{it} \right)
\]

where \( \alpha_i \) captures person-specific ability levels, \( \sum_{k=1}^{t-1} N_{ik} \) is total labor market experience gathered prior to period \( t \), \( \epsilon_{it} \) is person specific idiosyncratic shock to human capital production (for example, illness), and \( \beta_1 \) and \( \beta_2 \) capture returns
to accumulating experience. This gives me the following wage equation:

$$\ln w_{it} = \ln R_t + \beta_1 \sum_{k=1}^{t-1} N_{ik} + \beta_2 \left( \sum_{k=1}^{t-1} N_{ik} \right)^2 + \alpha_i + \epsilon_{it}$$  \hspace{1cm} (5)

It will be useful to write next period’s capital as a function of last period’s capital and hours worked:

$$K_{it+1} = \exp \left( \beta_1 \sum_{k=1}^{t} N_{ik} + \beta_2 \left( \sum_{k=1}^{t} N_{ik} \right)^2 + \alpha_i + \epsilon_{it+1} \right)$$

$$= \exp \left( \alpha_{it} + \epsilon_{it+1} + \beta_1 \sum_{k=1}^{t-1} N_{ik} + \beta_2 \left( \sum_{k=1}^{t-1} N_{ik} \right)^2 \right) + \left( \beta_1 + 2 \beta_2 \sum_{k=1}^{t-1} N_{ik} \right) N_{it} + \beta_2 N_{it}^2$$

$$= K_{it} \exp \left( \beta_1 + 2 \beta_2 \sum_{k=1}^{t-1} N_{ik} \right) N_{it} + \beta_2 N_{it}^2$$

$$= f(K_{it}, N_{it})$$

### 4.5 Equilibrium Solution

The agent’s decision problem can now be reformulated as the maximization of the following value function:

$$V^t(A_t, w_t) = \max_{N_t, C_t} U(L - N_t, C_t)$$

$$+ \beta E_t V^{t+1} \left( (1 + r_t)(A_t + w_t N_t - C_t) \cdot R_{t+1} f(w_t/R_t, N_t) \right)$$

Where $$V^t(A_t, w_t)$$ captures the maximum level of lifetime utility an agent can expect to obtain if he optimally allocates his decision variables $$N_t$$ and $$C_t$$ for
$t = 1, \ldots, T$, and $L$ captures total available hours that an individual can allocate between work and leisure.

First order conditions are:

$$
0 = E_t \left[ - \frac{\partial U_t}{\partial N_t} + \beta (1 + r_t) w_t \frac{\partial V_t^{t+1}}{\partial A_t^{t+1}} + \beta R_{t+1} \frac{\partial f_t}{\partial N_t} \frac{\partial V_t^{t+1}}{\partial w_{t+1}} \right]
$$

$$
0 = E_t \left[ - \frac{\partial U_t}{\partial C_t} + \beta (1 + r_t) \frac{\partial V_t^{t+1}}{\partial A_t^{t+1}} \right]
$$

Which, combined, gives the MRS condition:

$$
0 = E_t \left[ - \frac{\partial U_t}{\partial N_t} + w_t \frac{\partial U_t}{\partial C_t} + \beta R_{t+1} \frac{\partial f_t}{\partial N_t} \frac{\partial V_t^{t+1}}{\partial w_{t+1}} \right]
$$

Equation (6) allows us to examine the effects of human capital investment on the optimal labor supply choice. $-\frac{\partial U_t}{\partial N_t}$ denotes the loss to utility from increasing hours of work and $w_t \frac{\partial U_t}{\partial C_t}$ captures the utility gained from increased earnings and its effects on consumption. The final term, $\beta R_{t+1} \frac{\partial f_t}{\partial N_t} \frac{\partial V_t^{t+1}}{\partial w_{t+1}}$, captures the discounted increase in welfare due to higher wages in all future periods and is the main focus of this paper. $\frac{\partial f_t}{\partial N_t}$ is the increase in human capital stock from increased hours of work and $\frac{\partial V_t^{t+1}}{\partial w_{t+1}}$ measures the increase in welfare from an increase in the human capital stock. This term will be large if on-the-job learning significantly affects future wage rates. Note that human capital investment is not very important for people late in the life cycle. For them, the wage is close to the opportunity cost of time. Thus, later in the cycle, differences in hours work will largely be due to accumulated differences in wage growth.

The agent’s optimal allocation of resources over time also imply the
following:

\[
\frac{\partial V}{\partial A_t} = \beta (1 + r_t) \mathbb{E}_t \frac{\partial V^{t+1}}{\partial A_{t+1}} \tag{7}
\]

\[
\frac{\partial V}{\partial w_t} = \mathbb{E}_t \left[ \beta (1 + r_t) N_t \frac{\partial V^{t+1}}{\partial A_{t+1}} + \beta \left( \frac{R_{t+1}}{R_t} \right) \frac{\partial f}{\partial K} \frac{\partial V^{t+1}}{\partial w_{t+1}} \right] \tag{8}
\]

Using the FOC with respect to consumption, (8) can be rewritten as

\[
\frac{\partial V}{\partial w_t} = \mathbb{E}_t \left[ N_t \frac{\partial U}{\partial C_t} + \beta \left( \frac{R_{t+1}}{R_t} \right) \frac{\partial f}{\partial K} \frac{\partial V^{t+1}}{\partial w_{t+1}} \right] \tag{9}
\]

I can rewrite (6) with some substitutions using my FOC and equation (9) to obtain the following:

\[
0 = \mathbb{E}_t \left\{ \frac{\partial f_{t+1}}{\partial K_{t+1}} \left[ - \frac{\partial U_{t+1}}{\partial N_{t+1}} + w_{t+1} \frac{\partial U_{t+1}}{\partial C_{t+1}} \right] - \beta \frac{\partial f_{t+1}}{\partial N_{t+1}} \left[ \frac{\partial f_{t+1}}{\partial N_{t+1}} + w_{t+1} \frac{\partial U_{t+1}}{\partial C_{t+1}} \right] - R_{t+1} \frac{\partial f_{t+1}}{\partial N_{t+1}} N_{t+1} \frac{\partial U_{t+1}}{\partial C_{t+1}} \right\} \tag{10}
\]

Note that in expectation, the value of this function is zero, but actual realizations of future random variables imply that this will equal \( u_{t+1} \), and the property that \( \mathbb{E}_t u_{t+1} = 0 \) will be used to recover the structural parameters of the model.

Finally, we have a condition reflecting the trade-off an individual faces between consumption in period \( t \) and period \( t + 1 \) (i.e. the marginal rate of substitution in consumption over time):

\[
\mathbb{E}_t \left[ \frac{\partial U_{t+1}}{\partial C_{t+1}} \right] = \frac{1}{\beta (1 + r_t)} \tag{11}
\]
4.6 Estimation Methodology and Results

The estimation is done in two stages:

1. In the first stage, the wage equation is estimated to determine how wages grow with work experience.

2. In the second stage, the wage equation parameters are treated as known and the preferences parameters are estimated using GMM.

4.6.1 Stage 1: Human Capital Production Function

The structural parameters $\beta_1$ and $\beta_2$, as well as the rental rates for human capital and person-specific productivity can be estimated using wage equation (5), where $\ln R_t$ is captured in the time fixed effects and $\alpha_i$ is captured using person fixed effects. Productivity shock $\epsilon_{it}$ is modeled as a mean zero random variable and defined to be orthogonal to all observed arguments in the human capital production function.

Person fixed effects control for differences in innate ability that remain roughly constant over time, while I allow gains in human capital accumulation with my direct measure of experience. The correlation between experience and the error term could be limited to the individual fixed effect component $\alpha_i$. One interpretation of $\alpha_i$ is as a measure of the individual’s innate market productivity. If workers with innate market productivity specialize more in market production, and spend less time on household production and leisure, then $\alpha_i$ and experience will be positively correlated. If this is the extent of the issue, then fixed effects is a sufficient correction. However, this is unlikely.
tal variables are able to address additional standard issues plaguing observation studies like this one, including reverse causality (your wages will affect choices about hours worked, and thus the amount of experience you accumulate), time-varying unobserved heterogeneity (a health shock could effect hours worked and an individual's wages), and measurement error (concerns about measurement error around hours worked are well known, and will bias estimates of my parameter of interest towards zero).

To resolve these issues the wage equation is estimated using individual fixed effects combined with an instrumental variables approach, with age used as an instrument for experience\textsuperscript{21}. Age will effect the amount of experience someone has accrued, but arguably not earnings (controlling for experience). I assume that productivity shock $\epsilon_{it}$ is not revealed until after the worker decides on current hours of work. These regressions are run separately for black and white workers. OLS with fixed effect and IV results with fixed effects are reported in Table 15.

Table 15: Human Capital Production Function

<table>
<thead>
<tr>
<th>Parameter</th>
<th>IV</th>
<th>OLS</th>
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<tbody>
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<td>.026***</td>
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<td>.57,049</td>
</tr>
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</table>

\textsuperscript{21}Dustmann and Meghir (2005) also support the notion that age is an appropriate instrument for experience
I have

$$\frac{\partial f}{\partial K_{it}} = \exp \left( \beta_2 N_{it}^2 + N_{it} (\beta_1 + 2 \beta_2 \sum_{k=1}^{t-1} N_{ik}) \right)$$

$$\frac{\partial f}{\partial N_{it}} = \exp \left( \beta_2 N_{it}^2 + N (\beta_1 + 2 \beta_2 \sum_{k=1}^{t-1} N_{ik}) \right) K_{it} \left( \beta_1 + 2 \beta_2 N_{it} + 2 \beta_2 \sum_{k=1}^{t-1} N_{ik} \right)$$

To interpret the instrumental variable results from Table 15, note that the mean hours in the data for white workers is 1.97 thousands of hours, the mean hours of experience is 40.81 thousand, the mean wage is 26.14, and the mean person-level fixed effect is 3.12 (this would often be the constant term in a regression). Plugging these and the estimated values of my parameters gives $$\frac{\partial f}{\partial N_{it}} = 0.23$$.

This implies that an extra 1000 hours of work at time t (an increase in $$N_{it}$$ of 1) increases the wage rate at $$t+1$$ by 23 cents per hour for white workers. Changing only the values of $$\beta_1$$ and $$\beta_2$$ to those estimated for black workers, we instead have that an extra 1000 hours of work at time t increases the wage rate in $$t+1$$ by 12 cents.

### 4.6.2 Stage 2: Preference Parameters

I define $$L$$ as equal to the total number of potential annual hours to be utilized in any activity ($$365 \times 24$$), so that $$L_t = L - N_t$$, and $$\beta$$ is set to 0.97.

I estimate a translog utility function, which is a local second-order approximation to any arbitrary utility function (Christensen, Jorgensen, and Lau 1975). This has the advantage of being flexible, without imposing too many restrictions a priori, as individual leisure and consumption can be either substi-
tutes or complements. In particular, I have

\[ U_t = \ln L_t + \gamma_1 \ln C_t + \gamma_2 \ln L_t \ln C_t + \gamma_3 (\ln L_t)^2 + \gamma_4 (\ln C_t)^2 \]

where the coefficient on \( L_t \) is 1 for normalization. Given the functional form for the production function and utility function, I have

\[
\frac{\partial U_t}{\partial C_t} = \frac{1}{C_t} \left( \gamma_1 + 2\gamma_4 \ln[C_t] + \gamma_2 \ln[L - N_t] \right) \\
\frac{\partial U_t}{\partial N_t} = -\frac{1}{L - N_t} \left( 1 + \gamma_2 \ln[C_t] + 2\gamma_3 \ln[L - N_t] \right) \\
= -\frac{1}{L_t} \left( 1 + \gamma_2 \ln[C_t] + 2\gamma_3 \ln[L_t] \right)
\]

The basic idea behind the estimation strategy is to use the Euler equations to generate a set of population orthogonality conditions that depend in a nonlinear way on observables and on the unknown parameters characterizing preferences—call these \( \gamma_0 \). These orthogonality conditions are then used to construct a criterion function whose minimizer is the estimate of \( \gamma_0 \).

I combine the envelope conditions for the state variables with the first-order conditions to solve the optimization problem. I have the following two conditions defined by (10) and (11):

\[
\begin{align*}
\frac{\partial f_{t+1}}{\partial K_{t+1}} & - \frac{\partial U_{t+1}}{\partial N_{t+1}} + w_{t+1} \frac{\partial U_{t+1}}{\partial C_{t+1}} \\
\frac{\partial f_{t+1}}{\partial N_{t+1}} & - \frac{\beta}{\beta} \frac{\partial f_{t+1}}{\partial N_{t+1}} \left[ - \frac{\partial U_t}{\partial N_t} + w_t \frac{\partial U_t}{\partial C_t} \right]
\end{align*}
\]

\[
\begin{align*}
\frac{\partial U_{t+1}}{\partial C_{t+1}} & - \frac{\partial f_{t+1}}{\partial N_{t+1}} N_{t+1} \frac{\partial U_{t+1}}{\partial C_{t+1}} \\
\frac{\partial U_{t+1}}{\partial C_{t+1}} & - \frac{\partial U_{t+1}}{\partial C_{t+1}} + \frac{1}{\beta(1 + r_t)}
\end{align*}
\]
Assuming individuals behave rationally, I should have

\[ \mathbb{E}_t[u_{kit+1}] = 0 \quad \text{for } k = 1, 2 \]

i.e. \( u_{kit+1} \) is orthogonal to all elements in the individuals information set, denoted \( Z_{it} = \{z_{it1}, \ldots, z_{itL}\} \). Then

\[ \mathbb{E}_t[u_{kit+1}z_{jit}] = 0 \quad \forall j = \{1, \ldots, L\} \text{ and } k = \{1, 2\} \]

\[ \mathbb{E} \sum_{t=1}^{T} u_{kit+1}z_{jit} = 0 \quad \forall j = \{1, \ldots, L\} \text{ and } k = \{1, 2\} \]

And for large \( N \)

\[ O_N(\gamma_0) = \frac{1}{N} \sum_{i=1}^{N} \sum_{t=1}^{T} u_{kit+1}z_{jit} = 0 \quad \forall j = \{1, \ldots, L\} \text{ and } k = \{1, 2\} \]

Estimates for \( \gamma_0 \) are obtained by minimizing

\[ O_N(\gamma_0)'W_O N(\gamma_0) \]  

(17)

where \( W_N \) is a symmetric positive definite weighting matrix. In the first stage I estimate equation (17) via 2SLS and use the estimated residuals to form the second-stage optimal weight matrix for the GMM estimator.

Valid instruments are known to workers at time \( t \), so that they are uncorrelated with the forecast error \( u_{t+1} \). Valid instruments should also be uncorrelated with the human capital production shock \( \epsilon_{it} \). I will use as instruments a polynomial in current wages, leisure, consumption, and age, along with school-
ing, an interaction between schooling and age, leisure and wages, consumption and wages, state-level unemployment, and year dummies. Results are reported in Table 16.

Table 16: Preference Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\gamma_1$</td>
<td>0.0423</td>
<td>0.0042</td>
</tr>
<tr>
<td>$\gamma_2$</td>
<td>-0.0224</td>
<td>0.0020</td>
</tr>
<tr>
<td>$\gamma_3$</td>
<td>-0.2625</td>
<td>0.0024</td>
</tr>
<tr>
<td>$\gamma_4$</td>
<td>-3.7300e-04</td>
<td>1.3052e-04</td>
</tr>
<tr>
<td>J-stat</td>
<td>51.9204</td>
<td></td>
</tr>
<tr>
<td>test[df]</td>
<td>[80]</td>
<td></td>
</tr>
<tr>
<td>p-value</td>
<td>0.9937</td>
<td></td>
</tr>
</tbody>
</table>

The parameter estimates are reasonable, implying the marginal utility of leisure and consumption are both positive, with diminishing marginal returns for leisure. The estimate of $\gamma_4$ is insignificant. The estimate of $\gamma_2$, the cross-partial between leisure and consumption, is negative, indicating that leisure and consumption are substitutes in preferences, consistent with Shaw (1989), Ziliak and Kniesner (2005), and Hokayem and Ziliak (2014).

Given these parameter estimates, we can back out expected hours of work over the life-cycle for white workers and, holding utility preferences constant and using estimates for returns to experience for black workers, we can calculate expected hours of work and wages over the life-cycle for black workers and compare. This will give an estimate of how differences in returns to increased years of work experience alone change the hour profiles for black workers relative to white workers.
4.6.3 Simulations

The first order condition, combined with the laws of motion for human capital and assets, tells us how hours and wages move from one period to the next, conditional on a particular starting point. I conduct my simulations by setting the stochastic terms to zero and choosing appropriate first-period values for wages and hours\textsuperscript{22}. First period wage rates are set equal to the average initial human capital endowment for white workers (i.e. the average fixed effect of 3.12), and first period hours are set equal to the average hours for age 20 white individuals.

White workers have an incentive to work more in the early years of their career because they earn a greater return to experience in the form of higher future wages relative to black workers. Table 17 displays results for average annual hours worked and hourly wages, as well as lifetime income generated by the model for black and white workers.

\textsuperscript{22}Starting the simulations at the final year of full-time employment requires a final wage rate, an endogenous variable. This would constrain the optimal hours of work over the life-cycle, making comparisons between black and white workers impossible. More useful simulations will begin at time zero, conditional on initial hours and wages.
Table 17: Simulated Hours and Wages

<table>
<thead>
<tr>
<th></th>
<th>White</th>
<th>Black</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average annual hours worked (total)</td>
<td>1572.34</td>
<td>1562.02</td>
<td>10.32</td>
</tr>
<tr>
<td>( t \leq 20 )</td>
<td>1277.47</td>
<td>1273.71</td>
<td>3.76</td>
</tr>
<tr>
<td>( t &gt; 20 )</td>
<td>1867.21</td>
<td>1850.33</td>
<td>16.88</td>
</tr>
<tr>
<td>Average hourly wage (total)</td>
<td>25.94</td>
<td>25.21</td>
<td>0.73</td>
</tr>
<tr>
<td>( t \leq 20 )</td>
<td>24.02</td>
<td>23.75</td>
<td>0.27</td>
</tr>
<tr>
<td>( t &gt; 20 )</td>
<td>27.86</td>
<td>26.68</td>
<td>1.18</td>
</tr>
<tr>
<td>Lifetime Income</td>
<td></td>
<td></td>
<td>63,801</td>
</tr>
<tr>
<td>( t \leq 20 )</td>
<td></td>
<td></td>
<td>9,580</td>
</tr>
<tr>
<td>( t &gt; 20 )</td>
<td></td>
<td></td>
<td>54,222</td>
</tr>
</tbody>
</table>

Holding hours worked for black workers equal to hours worked for white workers, but allowing for differences in returns to experience, lifetime income increases by $11,694 for black workers. This can be interpreted as the difference in lifetime income due to differences in choices about hours worked, accounting for approximately 18% of the total explained differences in lifetime income.

Table 18: Explained Wage Differences

<table>
<thead>
<tr>
<th></th>
<th>White</th>
<th>Black</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simulated:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average hourly wage (total)</td>
<td>25.94</td>
<td>25.21</td>
<td>0.73</td>
</tr>
<tr>
<td>( t \leq 20 )</td>
<td>24.02</td>
<td>23.75</td>
<td>0.27</td>
</tr>
<tr>
<td>( t &gt; 20 )</td>
<td>27.86</td>
<td>26.68</td>
<td>1.18</td>
</tr>
<tr>
<td>Data (PSID):</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average hourly wage (total)</td>
<td>26.98</td>
<td>19.61</td>
<td>7.37</td>
</tr>
<tr>
<td>( t \leq 20 )</td>
<td>23.96</td>
<td>17.40</td>
<td>6.56</td>
</tr>
<tr>
<td>( t &gt; 20 )</td>
<td>30.92</td>
<td>23.18</td>
<td>7.74</td>
</tr>
</tbody>
</table>

Table 18 compares the average hourly wages for black and white workers measured in the PSID to those generated by the model. The average lifetime
hourly wage difference of 0.73 explains approximately 10% of average lifetime hourly wage differences measured in the PSID.

4.7 Conclusion

This paper has documented some important facts regarding returns to experience and hours worked for black and white workers. First, returns to an extra thousand hours of work experience for the typical white worker are 23 cents per hour in 2012 USD compared to 12 cents for an otherwise identical black worker. These differences in returns to experience generate a pattern of divergent wages between black and white workers over the life-cycle. Second, differences in returns to experience combined with simulated differences in choices of hours worked can account for approximately 10 percent of the measured difference in average wages over the life-cycle between black and white workers. The racial gap in returns to work experience both directly effects lifetime earnings, and indirectly effects lifetime earnings through induced differences in labor supply choices. The model shows that choices in hours worked explains approximately 18 percent of the generated differences in lifetime earnings, while the remaining 82 percentage is explained directly by differences in wage growth.

4.8 Bibliography


