Unequal Connections: Friendship Networks and Racial Labor Market Gaps*

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Abstract

We study how friendship networks contribute to racial labor market gaps in the United States. Black respondents report fewer close friends than White respondents, and this gap is larger in more residentially segregated states. We use this evidence to discipline an equilibrium model of costly friendship formation and job referrals. Reducing cross-race friendship barriers lowers Black unemployment by 1.8 percentage points, closing one third of the racial unemployment gap. Black workers' residual wages rise by 1.1 percent, closing about one fifth of the residual wage gap. These gains reflect changes in both the number of friends and their racial composition.

Keywords: Friendship networks, job referrals, racial unemployment gap, segregation.
JEL Classifications: D83, J15, J31, J64

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1 Introduction

Black-White gaps in wages and employment have persisted for decades in the United States (Cajner et al., 2017; Bayer and Charles, 2018), and are responsible for a broader and persistent disparity in economic well-being (Brouillette et al., 2025). Differences in education, age, occupation, and location can only explain part of these gaps, and other mechanisms that sustain them remain only partly understood (Daly et al., 2017). In this paper we focus on one such mechanism: racial differences in friendship networks and their consequences for labor market outcomes.

Black Americans have fewer friends than White Americans. In the Current Population Survey (CPS), Black respondents report 3.78 close friends, compared with 5.17 for White respondents, a gap of 1.4 friends. Other surveys with a similar question, such as the General Social Survey (GSS), American Community Life Survey (ACLS), and American Trends Panel (ATP), reveal similar racial gaps in the number of friends. This gap emerges in adolescence and continues into adulthood. In the National Longitudinal Study of Adolescent to Adult Health (Add Health), Black students in grades 7 through 12 report receiving 1.1 fewer best-friend nominations from their schoolmates than White students. Smaller friendship networks also tend to be more homophilous, and this association is stronger for Black respondents than for White respondents.

In this paper, we document that racial friendship gaps are linked to both residential segregation and labor-market outcomes. Residential segregation remains substantial (Logan and Parman, 2025) and can limit opportunities for cross-race contacts. We show that, across U.S. states, greater segregation is associated with a larger racial friendship gap. This relationship is driven by variation in segregation that traces back to the historical fragmentation of local governments (Cutler and Glaeser, 1997).

Differences in network may matter for employment, because personal contacts account for an estimated 30 to 60 percent of new hires (Topa, 2011; Ioannides and Datcher Loury, 2004). Using the CPS, we document that each additional friend is associated with a lower probability of unemployment, and states with larger friendship gaps also exhibit larger Black disadvantages in unemployment rates and duration.

We then quantify how barriers to cross-race friendship formation contribute to racial unemployment and wage gaps. We build a general equilibrium model in which workers make costly effort to form same-race and cross-race friendships. We model barriers to cross-race friendship formation through a reduced-form wedge in the meeting technology, which we map to observed residential segregation. Workers learn about vacancies either directly or through employed friends, who pass unused leads to one unemployed friend. The value of a contact therefore depends on the probability that she is employed and on competition from her other unemployed friends. Better job finding prospects, which depend on the number of friends, strengthen workers' outside options in wage bargaining. In turn, employment prospects and wages determine the returns to networking. Friendships, unemployment, wages, and vacancy creation are thus jointly determined.

We discipline the model using data from 42 state-level labor markets, where Black adults constitute at least 1% of the prime-age Black–White labor force. We target the state-level unemployment rates, unemployment duration, and residual hourly wages in each state, together with aggregate friends counts by race. We take the observed segregation in each state, which in the model affects the formation of inter-racial friendships, as given, and use the relation between friendship gap and segregation across states to estimate cross-race barriers through indirect inference.

The calibrated model serves as a laboratory to assess how much social segregation matters for friendship formation and, in turn, for labor market outcomes. We reduce residential segregation in each state to that of the least segregated state in the sample, Alaska, while holding all other parameters and exogenous inputs fixed. On average, Black unemployment duration declines by 5.7 weeks and unemployment rate falls by 1.8 percentage points, narrowing the racial unemployment gap by about one third. Their residual hourly wages rise by 1.1 percent, closing the residual racial wage gap by about one fifth. In the model's income-based measure, welfare net of networking costs rises by 2.1 percent for Black workers.

Both the number and composition of friendships adjust. Black workers gain 2.10 friends on average, compared with 0.37 for White workers, and both groups substitute cross-race for same-race friendships. Cross-race links connect one worker from each

group, so a given increase in these links adds more friends per worker to the smaller group. Changes in the composition of friendships also change access to employed contacts and competition for their leads, which can lead to substantial employment gains even where the gap in the total number of friends changes little.

Our analysis relates to four strands of the literature. First, research on racial inequality documents persistent differences in intergenerational mobility (Chetty et al., 2020) and career wage growth (Daly et al., 2020).[1] Quantitative studies emphasize pre-market endowments and human-capital accumulation (Rauh and Valladares-Esteban, 2023), and employer discrimination in frictional labor markets (Cairó and Lipton, 2026). We examine a complementary mechanism: unequal access to job information through endogenous friendship networks.

Second, we build on models of referrals and labor market inequality (Calvó-Armengol and Jackson, 2004, 2007; Calvó-Armengol and Zenou, 2005).[2] Galenianos (2021) endogenizes referral networks and shows how their structure amplifies inequality, while Bolte et al. (2026) link homophilous referrals to inequality and immobility. Miller and Schmutte (2021) and Treanor (2023) study how segregated referral networks shape racial hiring, occupations, and wage gaps, taking network size and composition as given. We instead model costly friendship formation, allowing both the number and racial composition of friends to respond to labor market returns. We use observed racial friendship counts and their relationship with residential segregation to discipline this formation process and quantify how reducing barriers to cross-race friendships affects unemployment and wages.

Third, we relate to work on friendship formation and the economic value of social ties.Currarini et al. (2009, 2010) show how group size, meeting opportunities, and preferences shape networks. Chung and Kim (2024) study friendship deficits among high-achieving Black students, and Lleras-Muney et al. (2026) estimate bounds on earnings returns to adolescent friendships. Chetty et al. (2022a,b) relate cross-class connectedness

[1]Related work examines racial disparities in wealth (Derenoncourt et al., 2024), marriage and incarceration (Charles and Luoh, 2010), and violent crime (Sampson et al., 2005).

[2]Empirical evidence on referrals, hiring, earnings, and racial segregation across firms includes Mouw (2002) and Bayer et al. (2008); Schmutte (2015); Dustmann et al. (2016).

to mobility and distinguish exposure from friendship choice. We derive the returns to same-race and cross-race adult friendships from job finding and wage bargaining, without imposing an intrinsic preference for same-race friends.

Finally, research links residential segregation to racial disparities (Cutler and Glaeser, 1997; Ananat, 2011) and school friendships (Mouw and Entwisle, 2006), while childhood interracial exposure has lasting effects on adult relationships and residential choices (Merlino et al., 2019, 2024). Quantitative equilibrium models study how residential sorting and educational spillovers amplify inequality (Fogli et al., 2026), and how housing vouchers and place-based policies affect children's skills and welfare (Chyn and Daruich, 2025). We isolate an adult labor market channel: barriers to cross-race friendship formation associated with segregation alter access to vacancy information.

2 Empirical Facts

This section documents the empirical links between friendship networks, residential segregation, and racial labor market inequality. We first document Black–White differences in the number of friends. We then show that individuals with more friends are less likely to be unemployed. Across US states, we show that larger racial friendship gaps are associated with wider racial gaps in unemployment rates and duration. Finally, we examine whether racial friendship gaps are larger in more segregated states.

2.1 Data

We focus on Black and White labor-force participants aged 25-55, and restrict our analysis to US states where Black workers account for at least 1 percent of the Black-White labor force in the 2008-2018 American Community Survey (ACS; Ruggles et al., 2025). This restriction leaves 42 state-level markets, including the District of Columbia.[3] For these 42 states, we measure the number of close friends using the November 2008 Current Population Survey (CPS; Flood et al., 2025), unemployment duration using the 2008-2018

[3]The states we exclude are: Maine, New Hampshire, Vermont, Idaho, Montana, North Dakota, South Dakota, Utah, and Wyoming.

CPS, and unemployment rates using the 2008-2018 ACS.[4] Finally, we construct a residential segregation measure for each state using the 2010 Census. The General Social Survey (GSS), American Community Life Survey (ACLS), and American Trends Panel (ATP) provide additional sources for measuring adult friendships.[5]

We complement CPS measures of the number of friends and labor market outcomes with the National Longitudinal Study of Adolescent to Adult Health (Add Health; Harris and Hummer, 2026), which follows a nationally representative cohort of students enrolled in grades 7-12 in 1994-1995 into adulthood. Wave I provides friendship nominations received from schoolmates; Waves IV (when survey participants are between ages 25 and 33) and V (when they are between 33 and 44) report adult close-friend counts and labor market outcomes. Wave IV also asks respondents about the racial composition of their close friends.

Throughout this section, racial gaps are defined as White minus Black: a positive friendship gap indicates more friends among White respondents, while negative unemployment rate or duration gaps indicate a Black disadvantage. Appendix A.1 provides further details on different data sources.

2.2 Racial Differences in Friendship Networks

We begin by documenting racial differences in the number of friends across surveys and then examine how the number of friends relates to the racial composition of friends. Black respondents report an average of 3.78 close friends in the CPS, compared with 5.17 for White respondents, a gap of 1.39 (Table 1, column (1)). The medians are three and five, respectively, so the gap appears not to be driven by the upper tail. Mean friendship counts are also lower for Black respondents in the other adult surveys, with gaps ranging between about 0.5 and 1.5 friends. In Add Health, Black respondents receive about one fewer friendship nomination as students (Wave I) and report fewer close friends as adults (Waves IV and V).

[4]Respondents were asked to provide a number of close friends. Close friends were described to respondents as "people you feel at ease with, can talk to about private matters, or call on for help".

[5]Because US state identifiers are not available, neither Add Health nor the other three surveys is restricted to the 42 states.

Table 1: NUMBER OF FRIENDS BY RACE ACROSS SURVEYS

						Add-Health		
		CPS	GSS	ACLS	ATP	Wave I	Wave IV	Wave V
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mean num. friends	Black	3.78	10.74	3.81 [3.63]	3.81 [3.63]	3.96	3.90	2.92
Mean num. friends	White	5.17	12.25	4.54 [4.34]	4.40 [4.10]	5.07	5.15	3.63
Median num. friends	Black	3.0	7.0	3.0	3.0	3.0	3.0	1.5
Median num. friends	White	5.0	8.0	4.0	4.0	4.0	4.0	4.0
Ages		25-55	25-55	25-55	18-64	12-21	25-33	33-44
Year		2008	2002	2021	2023	1994-1995	2008-2009	2016-2019
N		24970	662	2011	2978	7363	7586	7581

SOURCES: CPS, GSS, ACLS, ATP, and Add Health; Appendix A.1.
NOTES: Means are survey-weighted, and medians unweighted, except that unbracketed ACLS/ATP statistics use fitted negative binomial distributions; brackets show censored means. Add Health measures received nominations in Wave I and self-reported number of friends in Waves IV-V.

The number of friends varies depending on the racial composition. In Add Health Wave IV, White respondents who report that at least half of their close friends are of another race have, on average, 0.44 more friends than White respondents below that threshold. The corresponding difference among Black respondents is 1.04 friends (Table A.2, column (2)): having predominantly same-race friends is associated with smaller friendship networks, especially for Black respondents.

2.3 Friendships and Labor Market Outcomes

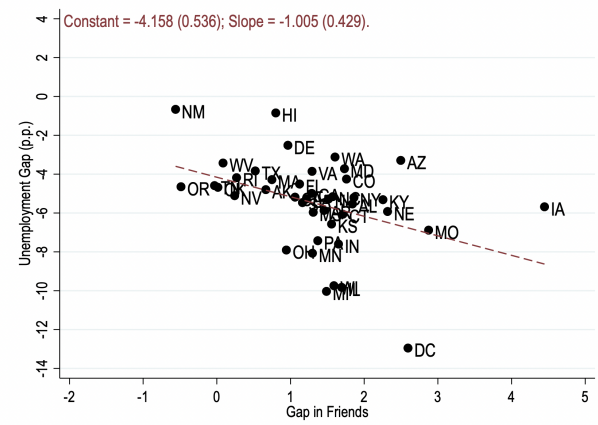
Next, we examine how friendships relate to labor market outcomes, first at the individual level and then across states.

Individual-level evidence. In the 2008 November CPS sample, having one additional friend is associated with a 0.27 percentage point lower probability of being unemployed, conditional on age, gender, race, and education (Table A.3). The unemployment rate in the sample is 6.1 percent. Add Health provides complementary evidence. Controlling for demographic characteristics, as well as school fixed effects and Big Five personality traits, an additional friend is associated with a 0.2-percentage-point lower probability of nonemployment in Wave IV and a 0.6-percentage-point lower probability in Wave V (Appendix A.2.3).

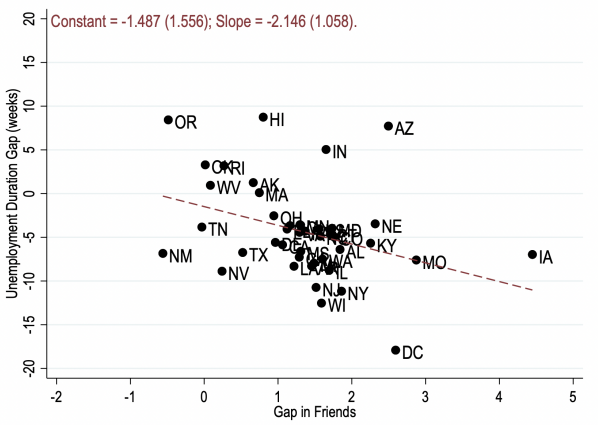
State-level racial gaps. Figure 1 shows that US states with larger White-Black friendship gaps also have larger racial gaps in unemployment. There is a wide variation in friendship gaps across states; in states such as Oregon and New Mexico, there are basically no gaps, while gaps are larger than two friends and a half in Missouri and Iowa. Having one fewer friend for Blacks relative to Whites is associated with a 1-percentage-point wider unemployment gap and about two additional weeks of unemployment duration for Black relative to White workers. These associations are robust to controlling for state population, college share, the Black share, and state-level average wage (Table A.5, column (2))

Figure 1: RACIAL FRIENDSHIP GAPS AND UNEMPLOYMENT GAPS

(A) UNEMPLOYMENT RATE



(B) UNEMPLOYMENT DURATION



SOURCES: November 2008 CPS friendship counts; 2008–2018 ACS unemployment rates and CPS duration.
NOTES: Points represent the 42 state-level markets, including DC. Gaps are White minus Black. Horizontal axes show friendship-count gaps, vertical axes show unemployment rate gaps in percentage points (panel A) and duration gaps in weeks (panel B). Negative vertical values indicate a Black disadvantage. Dashed lines are OLS fits without controls. Annotations report the estimated OLS coefficients and heteroskedasticity-robust standard errors (in parentheses).

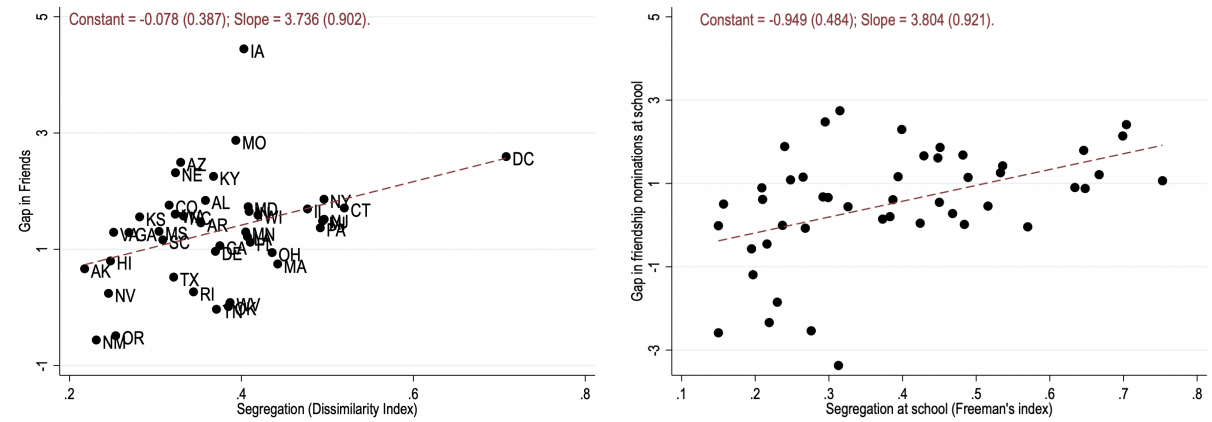
2.4 Residential Segregation and the Racial Gap in Friends

Finally, we examine whether racial friendship gaps are larger in states with greater residential segregation. Meeting opportunities and friendship choices can shape both the number and racial composition of friends (Currarini et al., 2009; Chetty et al., 2022b).

We measure state-level residential segregation, D_s, as the population-weighted average of county-level dissimilarity indices, which capture Black-White residential sorting

Figure 2: SEGREGATION AND THE RACIAL GAP IN FRIENDS

(A) ACROSS STATES (CPS) **(B)** ACROSS SCHOOLS (ADD HEALTH)



SOURCES: November 2008 CPS, 2010 Census tract counts (NHGIS), and Add Health Wave I.
NOTES: All gaps are White minus Black. Panel A plots mean friendship-count gaps against residential dissimilarity in 42 state-level markets, including DC. Panel B plots gaps in received friendship nominations against segregation within school friendship networks as measured by the Freeman index. Each point represents a state-level market (A) or a school (B). Dashed lines show OLS fits without controls; annotations report the estimated coefficients and heteroskedasticity-robust standard errors (in parentheses).

across census tracts within counties (Appendix A.1.4), and estimate:

$$\Delta F_s = \beta_0 + \beta_1 D_s + X_s'\gamma + \varepsilon_s, \tag{1}$$

where ΔF_s is the White-Black difference in mean friendship counts in state s. The vector X_s includes state population, the college-educated share, the Black share of the Black-White labor force, and average hourly wages; ε_s is an error term.

Panel A of Figure 2 shows the relationship without any controls. The OLS coefficient of 3.736 implies that a 0.1 increase in dissimilarity is associated with a larger White-Black friendship gap of 0.37 friends. Hence, moving from a less segregated state like Alaska, with a dissimilarity index of 0.22 to a more segregated state like New Jersey, with a dissimilarity index of 0.5, is associated with a 1.05 higher friendship gap between Blacks and Whites. Adding controls yields similar estimates (Table A.6, columns (1)-(2)).[6]

[6]The results are robust to using a state-level dissimilarity index with population over tracts. See Table A.7 in Appendix A.2.4.

Instrumental-variables evidence. In Figure 2, unobserved state characteristics may affect both outcomes, while friendship networks may themselves influence residential choices. To address these concerns, we complement the OLS analysis with an instrumental-variables strategy, adapting the approach of Cutler and Glaeser (1997). We instrument D_s with the logarithm of the number of municipal and township governments in 1962 per unit of state land area. The idea behind this instrument is that greater fragmentation creates more jurisdictions across which households can sort, potentially encouraging residential segregation through differences in local taxes and public services. Identification requires that historical fragmentation affect current racial friendship gaps only through measured residential segregation, conditional on state controls. Appendix A.2.5 discusses this exclusion restriction and its potential violations.

Historical government density predicts higher contemporary segregation: moving to a US state with twice the density of local governments increases the dissimilarity index by 0.026 without controls and 0.024 with controls, corresponding to roughly one-third of a standard deviation in segregation across states. The F-statistics of 73.70 and 48.67 suggest significant power of the instruments (Figure A.1; Table A.6, columns (3)-(4)). The second-stage IV estimates are 4.475 without controls and 3.792 with controls: a 0.1 increase in dissimilarity therefore corresponds to estimated increases of 0.45 and 0.38 friends in the racial gap, respectively. Both estimates are close to their OLS counterparts.

School friendship networks. Panel B of Figure 2 provides complementary evidence from the Add Health dataset. It relates the White-Black gap in received friendship nominations to segregation within school friendship networks, measured using the Freeman segregation index.[7] The relation is statistically significant at 1 percent: a 0.1 increase in this index is associated with a 0.38-nomination larger gap.

[7]The Freeman index measures segregation in a network by comparing observed cross-group ties with those expected under random mixing. See Appendix A.1.4.

2.5 Taking Stock

Across surveys, Black respondents have smaller friendship networks. Larger networks are associated with better employment outcomes at the individual level, and larger racial friendship gaps across states accompany wider gaps in unemployment rates and duration. Friendship gaps are also larger in more segregated states.

These patterns motivate the equilibrium model developed in the next section. The number and composition of friends affect access to vacancies and wages, while labor market conditions shape the incentives to form friendships in environments where friendship formation is subject to barriers. The model captures these interactions. In the quantitative analysis, we map barriers to cross-race friendship formation to observed residential segregation and assess their effects on racial labor market gaps.

3 Model

We build a general equilibrium model in which workers form friendships through costly effort and find jobs either directly or through referrals from their employed friends. The role of personal contacts in transmitting job information is central to the literature on labor market referrals (Topa (2011) and Ioannides and Datcher Loury (2004) provide reviews). The number and composition of friendships determine access to job information and affect wages through workers' outside options. In turn, labor market conditions affect both the likelihood that friends can provide referrals and the returns to forming new friendships. The model therefore allows friendships, employment, wages, and vacancy creation to be jointly determined. We capture barriers to cross-race friendship formation through a reduced-form wedge in the meeting technology. In the quantitative analysis, we map this wedge to observed residential segregation.

3.1 Environment

Time is discrete and infinite, and a period is one month. The economy is populated by a unit mass of risk-neutral workers and a large measure of potential one-job firms. All

agents discount the future by $\beta \in (0,1)$. Workers belong to groups $r \in \{b,w\}$, with population shares $\mu_r > 0$ and $\mu_b + \mu_w = 1$.

Workers supply labor inelastically and are either employed or unemployed. Employed workers from group-r produce y_r and receive wage w_r, determined through bargaining between firms and workers. Existing matches are destroyed at the end of a period with probability $\delta_r \in (0,1)$. Unemployed workers receive income b_r, with $0 \leq b_r < w_r$. Firms post vacancies at a per-period cost $c > 0$ and the mass of vacancies, $v \in (0,1)$, is determined by free entry.

Friendships are bilateral, every link represents one friend to each worker at either end of it. Let $n_{t,rg}$ denote a group-r worker's realized number of group-g friends at time t, suppressing the worker index. Let N_{rg} denote the average of this count across all group-r workers. In a stationary equilibrium, these averages are constant even though individual friendship counts change.

Vacancy information reaches both employed and unemployed workers: unemployed workers use this information to find a job, whereas employed workers remain in their job and pass the lead to one of their unemployed friends (Calvó-Armengol and Jackson, 2004; Calvó-Armengol and Zenou, 2005). Thus, friendships give unemployed workers access to vacancies beyond those they hear about directly, and the employment status of their contacts determines which friendships can provide this additional source of job information.

At the beginning of a period, employment and friendships are given. Employed workers earn wages, and unemployed workers receive b_r. Vacancy information arrives and can be passed through existing friendships. At the end of the period, existing jobs are destroyed with probability δ_r, existing friendships dissolve with probability $\lambda \in (0,1)$, and new friendships are formed. New job matches and friendships become active in the following period.

3.2 Friendship Formation

We model friendship formation following Currarini et al. (2009, 2010), who show how meeting opportunities and preferences over friends' types jointly determine network size and composition. Here, we derive the returns to friendships from job finding and wage bargaining. Friendships provide no direct utility, and workers have no intrinsic preference for same-race friends.

Consider workers of group r. They choose how much effort $e_{rg} \geq 0$ to direct toward each group $g \in \{b, w\}$. We restrict attention to effort choices that are stationary and do not depend on a worker's employment status or realized network. We determine these choices in Section 3.5, after deriving their labor market returns.

We focus on equilibria that are symmetric within each group: all group-r workers choose the same effort pair (e_{rb}, e_{rw}). Equal effort within a group does not imply identical networks, as random friendship formation and dissolution generate differences in the number and racial composition of friends across workers and over time.

Meetings. Each meeting produces a friendship. Conditional on effort, the number of new group-g friendships a worker forms during a period is Poisson with mean m_{rg}. The expected number of new same-race friends per worker and period is

$$m_{rr} = \bar{\eta}_{rr} e_{rr}, \tag{2}$$

where $\bar{\eta}_{rr} > 0$ measures the efficiency of same-race effort.

Cross-race friendship formation requires instead effort from both groups. Let $E_{rg} = \mu_r e_{rg}$ denote aggregate effort directed from group r toward group g. Each new cross-race friendship pairs one worker from each group. Within a group, workers are selected in proportion to their cross-race networking effort. A group-r worker's expected number of new group-g friends per period is therefore given by

$$m_{rg} = \eta_x(D) \rho_{rg} e_{rg}, \qquad \rho_{rg} = \frac{E_{gr}}{E_{rg} + E_{gr}}, \qquad r \neq g, \tag{3}$$

where $\eta_x(D) = \bar{\eta}_x \exp(-\zeta D)$, $\bar{\eta}_x > 0$ and $\zeta \geq 0$. An individual worker takes ρ_{rg} as given.

This ratio measures effort from the other group relative to total cross-race effort.[8] The exogenous index $D \geq 0$ captures barriers to forming cross-race friendships, a higher D reduces the meeting rate when $\zeta > 0$, for a given level of effort. The aggregate flow of new cross-race friendships, which is the same for either group, is then

$$L_{bw} = L_{wb} = \eta_x(D) \frac{E_{bw} E_{wb}}{E_{bw} + E_{wb}}. \tag{4}$$

In a symmetric equilibrium, all workers within a group exert the same cross-race effort. Selection for new cross-race friendships is therefore uniform within that group and does not favor workers who already have more friends. Conditional on fixed efforts and aggregate conditions, we assume that a worker's numbers of new friendships with the two groups are independent, and that they are independent across periods and do not depend on her existing network.

Dissolution and stationary networks. Existing links dissolve independently with probability λ. Thus, in stationary equilibria

$$n_{rg} = s_{rg} + A_{rg}, \qquad s_{rg} \sim \text{Bin}(n_{rg}, 1-\lambda), \qquad A_{rg} \sim \text{Poisson}(m_{rg}), \tag{5}$$

where s_{rg} counts the worker's existing group-g friendships that survive into the next period, and A_{rg} counts new group-g friendships. Given n_{rg}, s_{rg} and A_{rg} are independent, that is, losing existing friends does not affect the arrival of new ones. With constant effort, a worker's stationary counts of Black and White friends are independent Poisson variables with means

$$N_{rg} = \frac{m_{rg}}{\lambda}.$$

Formation replenishes the friendships lost through dissolution. Because each cross-race friendship involves one Black worker and one White worker, the network satisfies

$$\mu_b N_{bw} = \mu_w N_{wb} = \frac{L_{bw}}{\lambda}.$$

[8] The cross-race meeting flow is zero if either group supplies no cross-race effort. When both aggregate efforts are zero, we set $L_{bw} = L_{wb} = 0$ and $\rho_{bw} = \rho_{wb} = 0$.

Consequently, a given mass of cross-race friendships provides more cross-race friends per worker in the smaller group.

3.3 Job Finding and Aggregate Matching

We now describe how the friendship networks formed above affect job finding. We model information transmission following Calvó-Armengol and Zenou (2005): employed workers pass unused vacancy leads to one of their unemployed friends, if they have any. Therefore, a worker's access to referrals depends on both the number and racial composition of her friends, since employment rates can differ across groups and unemployed friends do not pass vacancies on. As Bolte et al. (2026) emphasize, differences in group employment can generate unequal referral opportunities and reinforce employment disparities when ties are concentrated within groups.[9]

Information transmission. Each worker receives at most one direct vacancy lead per period, with probability v, regardless of race or employment status. An unemployed worker accepts a direct lead. An employed worker remains in her job and passes the lead to one of her unemployed friends, chosen with equal probability. If she has no unemployed friends, the lead is lost. Referral decisions use employment statuses at the beginning of the period. An unemployed worker may receive several referrals, but can accept only one job.

We use a mean-field approximation to compute job finding from group-level unemployment rates and friendship distributions, which avoids tracking every worker's network and employment history.

Let u_r denote the unemployment rate in group r. Conditional on race, we treat contacts' employment statuses as independent of one another and of realized friendship counts. A group-g friend is assigned unemployment probability u_g, regardless of the recipient's employment status. We use the same stationary Poisson distributions of friendship-counts for unemployed workers as for their group as a whole. Referrals from different

[9] Calvó-Armengol and Zenou (2005) take the number of contacts as given and redraw contacts each period. Here, friendship counts and composition are endogenous and links persist until they dissolve.

friends are treated as independent of one another and of direct vacancy leads.[10]

Consider an unemployed worker i and an employed group-g friend j who has a direct vacancy lead. Let K_g be the number of j's unemployed friends other than i. Workers with more friends are more likely to be reached through a friendship. For the independent Poisson friendship counts in our model, however, accounting for this selection and excluding the link to i leaves independent Poisson counts of other friends with the same means N_{gb} and N_{gw} (Newman et al., 2001). Under our employment-independence assumptions,

$$K_g \sim \text{Poisson}(\Lambda_g), \qquad \Lambda_g = \sum_{k \in \{b,w\}} N_{gk} u_k, \tag{6}$$

where Λ_g is the expected number of j's other unemployed friends. With K_g other potential recipients, i receives the lead with probability $1/(1+K_g)$. Averaging over K_g, the probability that j selects i is

$$p_g = \mathbb{E}\left[\frac{1}{1+K_g}\right] = \frac{1-\exp(-\Lambda_g)}{\Lambda_g}, \tag{7}$$

with $p_g = 1$ at $\Lambda_g = 0$. More unemployed friends mean more competition for the same lead, reducing the probability that any particular friend receives it. Under these assumptions, p_g depends on the group of the sender, not the recipient.

The probability that any given group-g friend passes a lead to a particular unemployed worker is then

$$\pi_g = v(1-u_g)p_g. \tag{8}$$

A useful contact is therefore one who is likely to be employed and to have fewer unemployed friends that compete for leads.

[10] Workers with fewer friends may remain unemployed longer and therefore be overrepresented among job seekers. Persistent links may also generate correlations between friends' employment histories. We abstract from both effects.

Job finding. For an unemployed group-r worker, averaging over her Poisson friendship counts gives the probability of receiving at least one referral:

$$P_r = 1 - \exp\left(- \sum_{g \in \{b,w\}} N_{rg} \pi_g \right). \tag{9}$$

The exponential term is the probability that none of her friends passes on a lead. Her job finding probability is

$$h_r = v + \chi(1 - v) P_r. \tag{10}$$

The first term is direct job finding. The second is job finding through receiving at least one referral. This can only happen if she receives no direct lead. Conditional on not meeting a vacancy directly and getting at least one referral, she meets a vacancy with probability $\chi \in [0,1]$. This parameter captures the effectiveness of received referrals in producing a match. Because of mean-field approximation, the probability h_r enters the unemployment inflows and outflows equations and the value functions. Holding referral probabilities and market conditions fixed, additional friends increase job finding with diminishing returns and network composition matters because groups can differ in π_g, such that equal numbers of friends need not provide equal access to vacancies.

Aggregate matching. Aggregate unemployment is $u = \sum_r \mu_r u_r$. The mass of matches with group-r workers is

$$M_r = \mu_r u_r h_r. \tag{11}$$

Writing $M = \sum_r M_r$, the probabilities that a vacancy is filled by a group-r worker and that it is filled at all are

$$q_r = \frac{M_r}{v}, \qquad q = \sum_r q_r = \frac{M}{v}. \tag{12}$$

Labor market tightness is $\theta = v/u$. Matching is generated by direct leads and referrals rather than imposed through an aggregate matching function. In a stationary equilib-

rium, unemployment inflows and outflows satisfy $(1-u_r)\delta_r = u_r h_r$, giving

$$u_r = \frac{\delta_r}{\delta_r + h_r}. \tag{13}$$

3.4 Value Functions and Wage Determination

Let V be the value of an open vacancy and J_r the value of a jobfilled by a group-r worker. Let W_r and U_r denote the worker's employment and unemployment values before networking costs. They satisfy

$$V = -c + \beta\Big[\textstyle\sum_{r\in\{b,w\}} q_r J_r + (1-q)V\Big], \tag{14}$$

$$J_r = y_r - w_r + \beta\big[(1-\delta_r)J_r + \delta_r V\big], \tag{15}$$

$$W_r = w_r + \beta\big[(1-\delta_r)W_r + \delta_r U_r\big], \tag{16}$$

$$U_r = b_r + \beta\big[h_r W_r + (1-h_r)U_r\big]. \tag{17}$$

For fixed stationary effort, networking costs are the same in both employment states, and subtracting their present value from both W_r and U_r leaves the employment surplus $W_r - U_r$ unchanged.

Wages are renegotiated every period through generalized Nash bargaining, taking the worker's networking policy as given. With worker bargaining weight $\alpha_r \in (0,1)$ and joint surplus $S_r = (W_r - U_r) + (J_r - V)$, bargaining implies

$$W_r - U_r = \alpha_r S_r, \qquad J_r - V = (1-\alpha_r)S_r. \tag{18}$$

Better job finding prospects raise the value of unemployment, so networks affect wages through the outside option even in jobs found directly.

3.5 Networking Decision

We now close the model by determining networking effort. An individual takes vacancy supply, group unemployment rates, friends' referral probabilities, and the cross-race ef-

fort ratios as given, but internalizes how her effort changes her own job finding probability and wage. Define the stationary mean number of group-g friends generated per unit of effort as

$$a_{rg} = \begin{cases} \bar{\eta}_{rr}/\lambda, & r = g, \\ \eta_x(D)\rho_{rg}/\lambda, & r \neq g. \end{cases}$$

A worker choosing (e_{rb}, e_{rw}) has stationary mean friendship counts $a_{rg}e_{rg}$ and job finding probability

$$h_r(e_{rb}, e_{rw}) = v + \chi(1-v)\left[1 - \exp\left(-\sum_{g\in\{b,w\}} a_{rg}e_{rg}\pi_g\right)\right]. \tag{19}$$

For a given job finding probability h, her stationary unemployment probability is $u_r(h) = \delta_r/(\delta_r + h)$, while $w_r(h)$ is the wage implied by (15)-(18). Stationary expected flow income is

$$\ell_r(h) = [1 - u_r(h)]w_r(h) + u_r(h)b_r.$$

Each worker chooses a permanent effort pair to maximize her expected income flow net of networking costs:

$$\max_{e_{rb}, e_{rw} \geq 0} \ell_r\big(h_r(e_{rb}, e_{rw})\big) - C_r(e_{rb}, e_{rw}),$$

where the per-period cost of effort, C_r is measured in income-equivalent units and equal to

$$C_r(e_{rb}, e_{rw}) = \sum_{g\in\{b,w\}} \frac{e_{rg}^{1+\nu_r}}{1+\nu_r}, \qquad \nu_r > 0.$$

For a positive effort choice, the first-order condition reads as

$$e_{rg} = (a_{rg}\mathcal{R}_{rg})^{1/\nu_r}, \qquad \mathcal{R}_{rg} = \frac{\partial \ell_r(h_r)}{\partial h_r}\chi(1-v)\pi_g(1-P_r). \tag{20}$$

Equation (20) equates the marginal cost of effort to its marginal income benefit, $a_{rg}\mathcal{R}_{rg}$. The term $\mathcal{R}_{rg} = \partial \ell_r/\partial N_{rg}$ is the marginal income gain from increasing the mean number of group-g friends, holding aggregate conditions fixed. Other things equal, contacts are more valuable when they transmit leads more often, when referrals are more likely to

produce a match, and when faster job finding yields larger income gains.

When $\zeta > 0$, higher D lowers the productivity of cross-race effort, so formation frictions are a source of racial friendship gaps, alongside group sizes, same-race meeting efficiencies, and labor market primitives. The equilibrium effect depends on both groups' effort responses and on changes in labor market conditions.[11] The quantitative analysis uses these joint adjustments to assess the labor market consequences of friendship differences.

4 Quantitative Exercise

We use the model to quantify how barriers to cross-race friendship formation affect racial labor market gaps. We first calibrate the model to the evidence presented in Section 2. We then lower the barriers associated with residential segregation and examine how friendships and labor market outcomes adjust.

Data and targets. We calibrate the model separately for each of 42 state-level labor markets using the empirical facts described in Section 2. The 2008-2018 ACS provides racial labor-force shares and unemployment rates. The 2008 November CPS sample and the 2008-2018 CPS samples provide unemployment duration over the same period, as well as friendship counts. We set each state's formation-friction index, D_s, equal to its residential dissimilarity index constructed from the 2010 Census. Appendix B.2 describes further details on calibration.

Calibration. A model period is one month. Several parameters are assigned based on a priori information. We set $\beta = 0.997$, corresponding approximately to an annual interest rate of 4 percent. Bargaining weights are assumed to be equal, $\alpha_b = \alpha_w = 0.5$ (as, for example, in Pissarides (2009)). Unemployment income is set to 40 percent of the average wage by race in the model economy (Hall, 2005; Hornstein et al., 2011). The monthly dissolution probability is $\lambda = 0.0087$, consistent with 48 percent of friendships surviving

[11] We report the definition of stationary competitive equilibrium in Appendix B.1.

after seven years, as documented by Mollenhorst et al. (2014). Finally, networking costs are assumed to be quadratic, hence $\nu = 1$. Table B.1 lists the assigned parameter values and their sources.

The remaining parameters are estimated using a method of simulated moments. Five of these estimated parameters are state-specific. First, the probability of receiving a vacancy v_s and the effectiveness of referrals, χ_s, are chosen to match the unemployment duration and the share of referrals among new hires. The data on unemployment duration in each state are presented in Figure B.4. For the share of referrals, we assume it is the same across states and set it at 50%. This value falls within the 30-60 percent range for the share of jobs found through friends or relatives, as reported in the review by Ioannides and Datcher Loury (2004, p. 1058). Second, separation probabilities $\delta_{r,s}$ are chosen so that the unemployment rate in each state matches the data in Figure B.3. The productivity of a match in each state by race, $y_{r,s}$, is chosen so that we match hourly residualized wages by race in each state.[12] Finally, the free-entry condition determines vacancy costs c_s.

The remaining four friendship-formation parameters $(\bar{\eta}_{ww}, \bar{\eta}_{bb}, \bar{\eta}_x, \zeta)$ are common across states. We discipline same-race meeting efficiencies, $\bar{\eta}_{ww}$ and $\bar{\eta}_{bb}$, using the average number of friends for each race, whereas we identify the cross-race meeting efficiencies, $\bar{\eta}_x$, and the sensitivity of cross-race formation to segregation, ζ, using the OLS estimates of the cross-state relationship between the White-Black friendship gap and residential dissimilarity, as reported in Figure 2A.[13] Appendix B.3 describes the procedure.

Benchmark fit. Table B.3 compares the targeted friendship moments with their model counterparts. The model generates 5.25 friends for White workers and 3.69 for Black workers, compared with targets of 5.17 and 3.78. The slope of the friendship gap on dissimilarity is 3.70, very close to the empirical estimate of 3.74. Appendix B.4 reports the estimated parameters and provides a full comparison between model and data targets.

[12] Wage targets use the pooled 2008-2018 ACS sample of Black and White wage-and-salary workers aged 25-55 with positive wage income and annual hours, excluding the self-employed. Hourly wages equal annual wage-and-salary income divided by annual hours. We adjust wages for calendar year, gender, college education, industry, occupation, and age, and normalize state-race means by the national adjusted mean for White workers. Appendix B.2 describes the construction.

[13] In Appendix C.2 we test the robustness of our quantitative exercise to targeting the IV estimates as reported in Table A.6, columns (5).

4.1 The Role of Residential Segregation

How much would racial labor market gaps narrow if workers in every state faced the same barriers to friendship formation of the least segregated state in our sample, Alaska? To answer this question, we impose $D_s = D_{\min} \equiv \min_{j \in \mathcal{S}} D_j, \forall s$, keeping all other model inputs and parameters at their baseline values. We then solve for a new stationary equilibrium in each state. Effort, network structure, job finding, wages, and vacancy creation all adjust.

Aggregate outcomes. Table 2 reports population-weighted average outcomes, using the weights defined in Appendix C.1. The Black-White unemployment rate gap narrows by about one third, from 5.5 to 3.7 percentage points. The duration gap falls by about 5.7 weeks, and the residual wage gap falls by about one fifth.

These reductions primarily reflect gains for Black workers. Their unemployment rate falls from 11.84 to 10.05 percent, and mean unemployment duration falls from 34.22 to 28.55 weeks. Their residual wage rises by 1.1 percent as improved job finding prospects strengthen their outside option. Changes for White workers are small: unemployment rises by 0.02 percentage points, duration by 0.10 weeks, and wages fall by 0.015 percent.

These labor market changes are accompanied by a substantial reallocation of friendships. Black workers gain 2.10 friends on average, compared with 0.37 for White workers, reversing the White-Black friendship gap from 1.56 to -0.18. Both groups acquire more cross-race friends and fewer same-race friends. Cross-race links connect one worker from each group, so an increase in these links adds more friends per worker to the smaller group. Among Black workers, the mean number of White friends increases from 0.51 to 3.70, while the mean number of Black friends falls from 3.18 to 2.10.

The small losses for White workers illustrate why more friends need not improve job finding in equilibrium. As cross-race friendships increase, workers gain new contacts, but competition for referrals also changes. An employed person that receives a direct vacancy lead passes it on to only one unemployed friend. When more unemployed friends compete for that lead, every one is less likely to receive it. This congestion can offset the benefit of additional contacts, leading to higher unemployment and longer spells.

Table 2: AGGREGATE OUTCOMES

	White			Black		
Outcome	Baseline	Counterfactual	Δ	Baseline	Counterfactual	Δ
Average number of friends	5.252	5.623	0.370	3.695	5.799	2.104
of which white friends	5.158	4.944	-0.214	0.512	3.700	3.188
of which black friends	0.094	0.679	0.585	3.182	2.099	-1.083
Average unemployment rate (%)	6.358	6.378	0.021	11.84	10.05	-1.795
Average unemployment duration (weeks)	27.98	28.08	0.100	34.22	28.55	-5.674
Average wage	1.004	1.004	-0.015%	0.948	0.959	1.099%
Welfare (gross)	321.9	321.8	-0.027%	293.6	300.2	2.229%
Welfare (net of networking costs)	316.3	316.2	-0.060%	286.5	292.5	2.106%

NOTES: Baseline and counterfactual columns report stationary model outcomes by race. The counterfactual sets $D_s = D_{\min}$, holding all other primitives at their baseline values. Averages are taken using race-by-state-population weights. Unemployment rates are in percent, duration is in weeks, and residual hourly wages in units of the baseline national residual mean for White workers. Δ is counterfactual minus baseline for counts and duration, a percentage-point change for unemployment, and a percentage change for wages and welfare. "Welfare (gross)" is discounted income before networking costs; net welfare deducts these costs. Appendix C.1 defines the weights and welfare measures.

Gross discounted income rises by 2.2 percent for Black workers and falls by 0.03 percent for White workers. After deducting networking costs, welfare rises by 2.1 percent for Black workers and falls by 0.06 percent for White workers.[14]

State-level outcomes. Figure 3 shows how the effects differ across states. In more segregated states, the reduction in barriers is larger, and the friendship gap tends to narrow more in states with higher baseline segregation (DC is an exception). The largest reduction in the unemployment rate gap is about 2.7 percentage points in Michigan (panel C).

Segregation alone, however, does not determine the size of these changes. States with similar dissimilarity indices can respond differently to the counterfactual because their racial population shares and calibrated labor market parameters differ. DC illustrates the role of relative group sizes. Black workers account for approximately 45 percent of its Black-White labor force, so new cross-race links add similar numbers of friends per worker to both groups. The friendship gap therefore changes little, even though DC has high baseline segregation. Yet its unemployment duration and unemployment rate gaps narrow by about five weeks and 1.8 percentage points, respectively. Thus, changes in the gap in total friendship counts need not capture changes in relative access to job information.

[14] Appendix C.1 provides definitions of welfare measures.

Panel D shows that the residual log wage gap narrows by up to 0.015, implying a 1.5 percent increase in Black wages relative to White wages. The average racial wage gap in the sample is about 5.6 percent. Panels E and F report welfare changes net of networking costs for Black and White workers, respectively. Black workers gain in every state when formation barriers fall, with gains reaching about 4.3 percent in Wisconsin. Changes for White workers are small and mostly negative: losses are generally below 0.1 percent

4.2 Race-Specific Labor Market Visibility.

In our benchmark model, the probability of finding a job for a race-r individual differ between races only through the probability of receiving at least one referral, P_r (equation (9)). As a result, the correlation between observed and simulated unemployment duration gap across states is 0.34 (Figure B.6, Appendix B.4). We extend the model to include race-specific visibility in the labor market and race-specific referral effectiveness:

$$h_r = \psi_r(v + \chi_r(1-v)P_r),$$

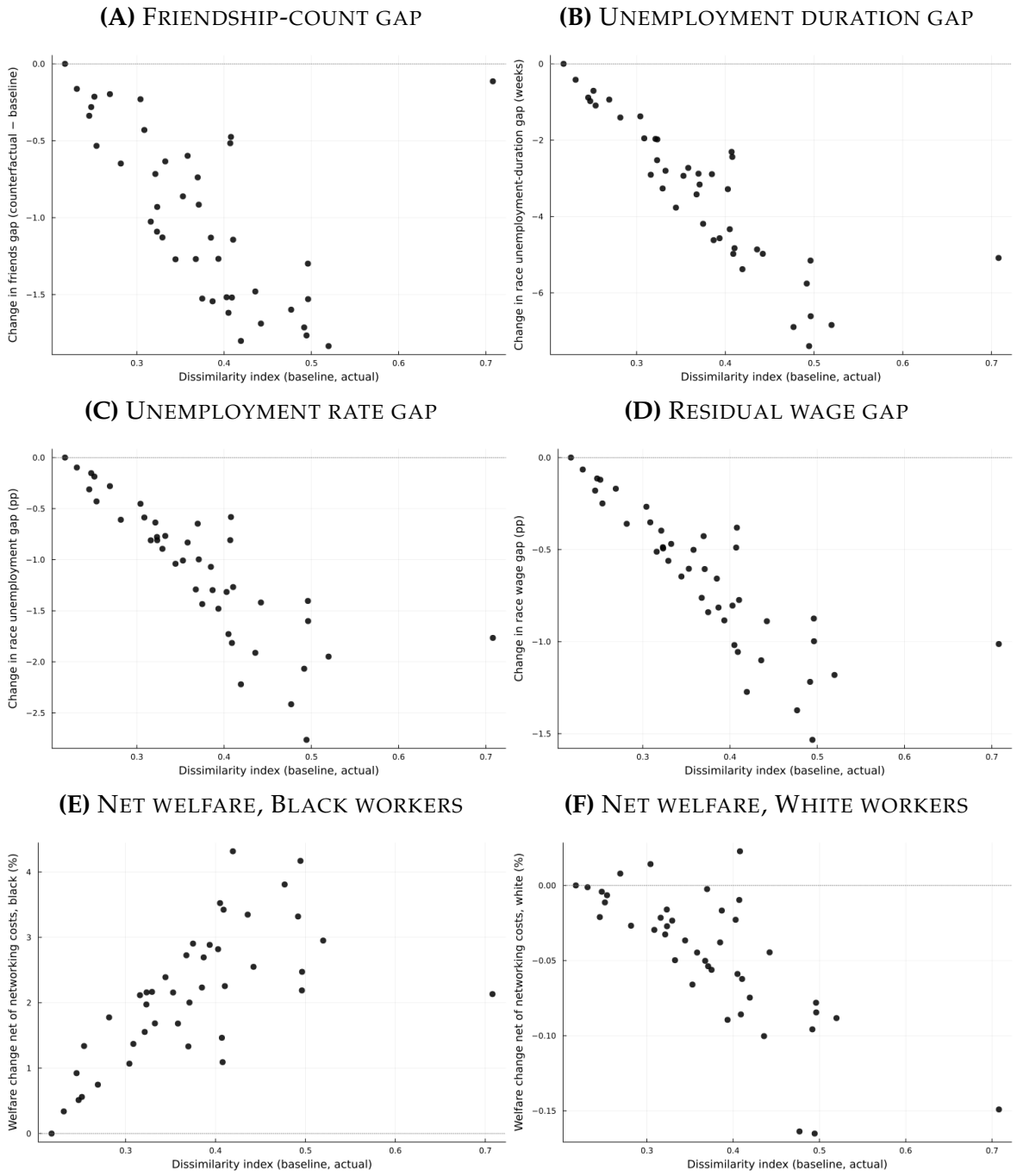
where $\psi_r > 0$ captures general matching efficiency in the labor market while $\chi_r \in [0,1]$ governs how effective referral leads are in producing a match.

To discipline them, first we construct race-by-state targets for referral use. Using the CPS for 2008–2018, we compute the share of unemployed job seekers who report contacting friends or relatives as a search method in the previous four weeks (Appendix A.1.2). The shares of referral-user are 0.258 among Black and 0.292 among White workers, around 55 percent of the benchmark target. We treat these shares as a proxy for the prevalence of referral-based hiring and target them to estimate χ_r separately by race and state.

Then, we normalize $\psi_w = 1$ in each state and estimate ψ_b jointly with the cost of posting vacancy c to match both Black and White-specific unemployment duration in each state. By construction, this version of the model captures the entire variation in the unemployment duration gap across states (Appendix C.3).

Under this alternative modeling structure, reducing segregation makes Black unem-

Figure 3: COUNTERFACTUAL OUTCOMES



NOTES: Each point represents a calibrated state-level market, including DC. Horizontal axes show baseline dissimilarity. The counterfactual sets $D_s = D_{\min}$ and holds all other primitives fixed. Panels A-D report counterfactual-minus-baseline changes: panel A in the White-Black mean friendship gap, in friends; panel B in the Black-White unemployment duration gap, in weeks; panel C in the Black-White unemployment rate gap, in percentage points; and panel D in $100 \times (\ln w_{w,s} - \ln w_{b,s})$, where wages use the baseline national residual White-wage normalization. Panels E and F report percentage changes in welfare net of networking costs for Black and White workers. Appendix C.1 defines the gaps and welfare measures.

ployment fall by about 1.3 percentage point and duration by 4.2 weeks (Appendix C.3, Table C.6). A lower targeted referral use limits the role of friendship network in the labor market: the gains in unemployment for Black workers are about three-quarters of those obtained in the benchmark even though their friendship counts increase slightly more than in the benchmark (2.76 versus 2.10). As a result, welfare increases by only 1.6 percent as opposed to 2.2 percent.

5 Conclusion

This paper quantifies the role of friendship formation in racial labor market inequality. We document smaller friendship networks among Black respondents and show that racial friendship gaps are associated with residential segregation and unemployment differences across states. We use these facts to discipline a general equilibrium model of costly friendship formation and job referrals. Reducing cross-race friendship barriers to those associated with the least segregated state in our sample lowers Black unemployment by 1.8 percentage points and raises Black workers' residual wages by 1.1 percent. The racial unemployment and residual wage gaps narrow by about one third and one fifth, respectively.

These gains reflect changes in both the number and racial composition of friendships. Better access to employed contacts improves job finding and strengthens workers' outside options, while competition for referrals limits the benefits of additional friends. Our findings highlight friendship formation as a quantitatively important channel linking residential segregation to racial labor market inequality.

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Online Appendix (not intended for publication)

A Data and Empirical Analysis

This appendix provides details on the data and empirical analysis underlying Section 2. Appendix A.1 describes the data sources, samples, and construction of key variables. Appendix A.2 presents the empirical specifications and results. Throughout the empirical analysis, racial gaps are always measured as White minus Black.

A.1 Data Sources and Variable Construction

A.1.1 American Community Survey

We use the 2008–2018 American Community Survey microdata (ACS; Ruggles et al., 2025). Person weights (PERWT) are used to construct each race's unemployment rate and the Black share of the Black-White labor force in each retained state. People are classified as employed or unemployed based on the EMPSTAT variable.

For wages, we retain private-sector wage-and-salary workers (CLASSWKR=2) with positive wage income (INCWAGE>0), usual weekly hours (UHRSWORK), and weeks worked (WKSWORK2). Hourly wages equal annual wage-and-salary income divided by annual hours, where annual hours are weeks worked times usual weekly hours. When weeks are reported in intervals, we assign the interval midpoint. Descriptive log-wage gaps, where used, are differences between weighted racial means of log hourly wages. The quantitative analysis instead uses residual wage levels, normalized by the national residual mean for White workers. The adjustment variables are calendar year, gender (SEX), college (based on EDUC), industry (IND), occupation (OCC), and age (AGE).

A.1.2 Current Population Survey

Friendship counts. The friendship question used in the analysis is from the November 2008 Current Population Survey (CPS; Flood et al., 2025):

> NOT COUNTING family members, about how many CLOSE FRIENDS do

you currently have, if any? These are people you feel at ease with, can talk to about private matters, or call on for help.

The number of friends takes positive values, including zero. We exclude refusals, "don't know" responses, and missing answers, and trim the number of friends above its 99th percentile. The analysis uses Black-alone and White-alone labor-force participants aged 25 to 55. We retain states in which Black workers account for at least 1 percent of the Black-White labor force, leaving 42 states, including the District of Columbia. Survey weights are used to calculate means by race and state.

Unemployment and Unemployment duration. We pool the 2008–2018 CPS (ASEC) to calculate mean reported unemployment duration, in weeks, among unemployed respondents for each state, and separately by race and state. We use DURUNEMP variable, which indicates for how many consecutive weeks each currently unemployed respondent had been without a job and looking for work.

We also use the November 2008 CPS to construct an individual-level indicator for unemployment. We use the variable EMPSTAT to identify respondents who are unemployed.

Job seekers through friends. We pool the 2008–2018 CPS (basic monthly) to compute the share of unemployed job-seekers that used friends and relatives during their job search. In particular, for Black-alone and White-alone respondents aged 25 to 55, and for the same 42 states as the rest of the analysis, that report being unemployed and having looked for jobs over the last 4 weeks (UH_LKFTPT_B2), we create a dummy that equals one if they report having contacted friends and relative as one of the methods of job search. Respondents are asked to list up to 6 job search methods (UH_LKM1_B1), and if they only report passive methods such as looking at ads, they are probed again to ask about any other methods they may have used (UH_LKPS1_B1). For any person that lists having contacted friends or relatives as a method of job search, either in the first question or in the follow up, we assign one to the dummy variable. We then use weights (WTFINL) to compute the aggregate share of job-seekers that report contacting friends or relative as

a method of job search.

A.1.3 Add Health

Study design. The National Longitudinal Study of Adolescent to Adult Health (Add Health; Harris and Hummer, 2026) follows a nationally representative cohort of U.S. adolescents enrolled in grades 7-12 during the 1994-1995 school year. Wave I combined an in-school questionnaire completed by approximately 90,000 students with detailed in-home interviews of 20,745 adolescents. The in-school component provides information on school friendship networks, while the in-home cohort is followed into adulthood. Individual records can be linked across waves and combined with information on families, schools, and neighborhoods. We use restricted-use data from Waves I, IV, and V. The official overview dates Wave IV to 2008 and Wave V to 2016–2018.[15]

Adolescent friendships. At Wave I, students could nominate up to five male and five female friends. Our adolescent friendship measure is *in-degree*: the number of nominations received from students in the same school. There is no cap on how many nominations a student can receive, and a received nomination need not be reciprocated.

Adult friendship counts. Waves IV and V ask about the number of close friends using the categories none, 1-2, 3-5, 6-9, and 10 or more. We assign values of 0, 1.5, 4, 7.5, and 11, respectively. The bounded positive categories use midpoints. For the 10 or more category, we use the mean number of friends with at least 10 friends in the 2008 November CPS sample.

Racial composition of adult friendships. Wave IV also asks about the racial composition of close friends, with responses ranging from "all your race" to "all other races." We construct an indicator equal to one for respondents reporting that at least half of their close friends are of another race, corresponding to "about half your race," "mostly other races," "almost all other races," and "all other races." The indicator is zero for the other

[15] See the Add Health study overview, https://addhealth.cpc.unc.edu/about/ (accessed October 18, 2026).

valid responses. By construction, respondents who report no close friends are excluded from the sample. Comparable information is unavailable in Wave V.

Adult labor market and demographic variables. Waves IV and V provide nonemployment outcomes. In Wave IV, respondents are classified as non-employed if they report zero annual personal earnings. This variable measures annual earnings before taxes, including wages, salaries, tips, bonuses, overtime pay, and income from self-employment. In Wave V, respondents are asked: "Are you currently working for pay?", and are classified as non-employed if they answered either "No, but have worked for pay in the past" or "No, have never worked for pay" to the question. Respondents who answered "Yes" are classified as employed.

Data for both waves report information on age, gender, race. Education, and the Big Five personality measures are taken from Wave IV and used as controls in both waves

A.1.4 Segregation Measures and Historical Government Data

Population and Residential segregation. We obtain 2010 Census tract counts from the National Historical Geographic Information System (NHGIS; Schroeder et al., 2026). Let j index tracts and i counties. Write B_j and W_j for Black-alone and White-alone tract populations, and B_i and W_i for the corresponding county totals. County dissimilarity is

$$d_i = \frac{1}{2} \sum_{j \in i} \left| \frac{B_j}{B_i} - \frac{W_j}{W_i} \right|. \tag{21}$$

For counties with positive populations in both groups, d_i is zero when the groups have the same distribution across tracts and one when they occupy separate tracts. This is the measure described by National Institute on Minority Health and Health Disparities (2026). State dissimilarity is the population-weighted county average,

$$D_s = \sum_{i \in s} \frac{p_i}{P_s} d_i, \tag{22}$$

where p_i denote county population, and

$$P_s = \sum_{i \in s} p_i, \quad \forall s \in \mathcal{S},$$

is the state-s population.

We compute the dissimilarity for counties with at least 100 Black residents. Within these counties, there may be tracts with only White or only Black residents. In a perfectly segregated county, all tracts would be populated either by only White residents or by only Black residents.

School friendship-network segregation. The school measure in panel B of Figure 2 is based on Freeman's segregation index (Freeman, 1978). It compares observed cross-race friendship ties with the number expected under random mixing. If race has nothing to do with friendship formation, then observed cross-race friendships should approximately equal their expected value under random mixing. Let n be the number of white-black links in a network. The index is then computed as

$$\text{FSI} = \frac{\mathbb{E}[n] - n}{\mathbb{E}[n]},$$

where $\mathbb{E}[n]$ is the expected number of cross trait ties, equal to the sum of the expected values for each possible trait-trait combination, omitting ties between nodes sharing a trait.

A value of zero of FSI denotes the random-mixing benchmark, whereas positive values indicate fewer cross-race ties than expected.

Historical government fragmentation. Historical counts come from Table 3 of Volume I of the 1962 Census of Governments (U.S. Census Bureau, 1962). Table A.1 reports the total number of local governments, the total excluding school districts, and the separate counts of municipal and township governments. Following the definition in Section 2.4, let G_s^{1962} be the sum of municipal and township governments in state s, and let A_s be state

land area. We construct our instrumental variable, Z_s as

$$Z_s = \log\left(\frac{G_s^{1962}}{A_s}\right). \tag{23}$$

A.1.5 Other Adult Friendship Surveys

Table 1 also uses the 2002 General Social Survey (GSS; Davern et al., 2025), the 2021 American Community Life Survey (ACLS; Survey Center on American Life, 2021), and the 2023 American Trends Panel Wave 131 (ATP; Pew Research Center, 2023). The GSS and ACLS samples cover ages 25-55, while the ATP sample covers ages 18-64.

The value of the number of friends from the 2002 General Social Survey is the sum of the responses to three questions regarding people other than family or relatives: 1) "Thinking about people at your workplace, how many of them are close friends of yours?", 2) "Thinking now of people who live near you — in your neighborhood or district: How many of these people are close friends of yours?", and 3) "How many other close friends do you have — apart from those at work, in your neighborhood, or family members? Think, for instance, of friends at clubs, church, or the like."

The value of the number of friends from the 2021 American Community Life Survey is the response to the question:

> If you counted the number of people you consider to be your close friend and who, in turn, would also consider you to be their close friend, how many people would that be?

The value of the number of friends from the 2023 American Trends Panel Wave 131 is the response to the question:

> Not counting your family, how many close friends do you have?

For the ACLS and ATP, we fit a negative binomial distribution separately by survey and race to adjust the friendship statistics for censoring at ten. The unbracketed entries in Table 1 are moments of these fitted distributions whereas bracketed entries retain the original censored means.

Table A.1: NUMBER OF LOCAL GOVERNMENTS IN 1962 BY STATE

State	All	All (excl. School Districts)	Municipalities	Townships
AL	732	618	349	0
AK	56	46	40	0
AZ	378	127	61	0
AR	1,208	791	417	0
CA	4,022	2,392	373	0
CO	1,193	881	253	0
CT	398	390	34	152
DE	207	117	51	0
DC	2	2	1	0
FL	764	697	366	0
GA	1,218	1,021	561	0
HI	20	20	1	0
ID	834	713	200	0
IL	6,452	4,912	1,251	1,433
IN	3,091	2,207	546	1,009
IA	2,642	1,306	944	0
KS	5,410	3,149	618	1,546
KY	872	664	365	0
LA	628	561	258	0
ME	658	632	21	470
MD	351	351	152	0
MA	586	557	39	312
MI	3,816	1,950	509	1,259
MN	5,212	2,869	845	1,822
MS	772	614	266	0
MO	3,726	2,077	892	329
MT	1,387	372	124	0
NE	5,124	1,860	537	478
NV	136	119	17	0
NH	550	329	13	221
NJ	1,395	883	334	233
NM	305	214	80	0
NY	3,802	2,571	612	932
NC	675	675	449	0
ND	3,028	2,042	356	1,387
OH	3,358	2,525	932	1,328
OK	1,959	734	533	0
OR	1,469	985	222	0
PA	6,201	4,022	1,003	1,555
RI	97	95	8	31
SC	552	443	255	0
SD	4,463	1,523	307	1,072
TN	657	643	280	0
TX	3,327	1,853	866	0
UT	423	383	212	0
VT	424	392	68	238
VA	380	380	236	0
WA	1,646	1,235	263	66
WV	389	334	224	0
WI	3,726	1,974	563	1,271
WY	464	257	90	0

SOURCE: 1962 Census of Governments, Volume I, Table 3.
NOTES: The first column reports US states abbreviation. The next four columns report all local governments, all local governments excluding school districts, municipalities, and townships.

A.2 Empirical Analysis

A.2.1 Friendship Size and Racial Composition

We use Add Health Wave IV to examine the association between the number and racial composition of close friends. We construct an indicator equal to one when respondents report that at least half of their close friends are of another race, corresponding to "about half your race," "mostly other races," "almost all other races," and "all other races." Let M_i denote this indicator, F_i the coded Wave IV number of close friends used elsewhere in the paper, and B_i an indicator for Black respondents. We estimate

$$F_i = \alpha + \beta M_i + \delta B_i + \gamma M_i \times B_i + \varepsilon_i.$$

Table A.2 reports the estimates. In column (1), respondents with at least half other-race close friends report 0.575 more close friends on average (s.e. 0.129). Black respondents report 1.206 fewer close friends than White respondents, conditional on friendship composition.

In column (2), for White respondents, having at least half other-race close friends is associated with 0.442 additional friends (s.e. 0.142). The interaction with the Black indicator is 0.600 (s.e. 0.294), implying an association of 1.04 additional friends for Black respondents. The interaction is significant at the 5 percent level. These results indicate a positive association between friendship size and racial composition, which is stronger among Black respondents.

A.2.2 Friendships and Unemployment in the CPS

We use the November 2008 CPS to examine the association of current friendship counts with unemployment at individual level. We estimate

$$Y_i = a + bF_i + X_i'\gamma + \varepsilon_i.$$

Here F_i is the reported friendship count. The outcome is an unemployment indicator among labor-force participants. The vector X_i contains age, gender, race, and education

Table A.2: NUMBER OF CLOSE FRIENDS AND RACIAL COMPOSITION OF FRIENDS

	Number of close friends	
	(1)	(2)
Black	-1.206***	-1.357***
	(0.128)	(0.139)
At least half other-race friends	0.575***	0.442***
	(0.129)	(0.142)
Black × At least half other-race friends		0.600**
		(0.294)
Controls	Yes	Yes
Observations	7,400	7,400

SOURCE: Add Health Wave IV.
NOTES: The dependent variable is the coded self-reported number of close friends. Responses of none, 1-2, 3-5, 6-9, and 10 or more are coded as 0, 1.5, 4, 7.5, and 11, respectively. Respondents report the racial composition of their close friends in seven categories ranging from "all your race" to "all other races." *At least half other-race friends* equals one for respondents reporting "about half your race," "mostly other races," "almost all other races," or "all other races," and zero for the other valid responses. Column (1) controls for respondent race; column (2) additionally interacts the indicator with the Black indicator. Wave IV sampling weights are used. Parentheses report school-clustered standard errors.. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

fixed effects. Table A.3 reports specifications with and without these controls.

Without controls, the coefficient is -0.0044: an additional friend is associated with a 0.44-percentage-point lower unemployment probability. Adding controls in column (2) reduces the magnitude of this association to 0.27 percentage points ($b = -0.0027$). The latter corresponds to 4.4 percent of the mean unemployment rate in the column (2) regression sample. Both coefficients are significant at the 1 percent level.

A.2.3 Friendships and Nonemployment in Add Health

We estimate separate regressions for Waves IV and V,

$$Y_{it} = a_t + b_t F_{it} + X_{it}'\gamma_t + \psi_{\sigma(i),t} + \varepsilon_{it}, \qquad t \in \{\text{IV}, \text{V}\},$$

where Y_{it} is a nonemployment indicator and F_{it} is the close-friend count reported in that same wave. School fixed effects, $\psi_{\sigma(i),t}$, absorb differences common to respondents assigned to the same school. Columns (1) omits individual controls; columns (2) adds age,

Table A.3: FRIENDS AND LABOR MARKET OUTCOMES: CPS

	Unemployed	
	(1)	(2)
Num. friends	-0.0044***	-0.0027***
	[0.0005]	[0.0005]
Controls	No	Yes
Observations	21,333	21,333

SOURCE: November 2008 CPS.
NOTES: Each column reports a separate regression of the outcome on friendship count. The outcome is an indicator for unemployment among labor-force participants. Columns (1) includes no controls; columns (2) add age, gender, race, and education fixed effects. The estimated coefficients are expressed in probability units. Brackets contain heteroskedasticity-robust standard errors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

gender, race, and education; columns (3) also includes the Big Five personality traits. Standard errors are clustered by school.

In the richest specifications, an additional friend is associated with a 0.2-percentage-point lower nonemployment probability in Wave IV and a 0.6-percentage-point lower probability in Wave V (Table A.4, column 3). These are equivalent to 3.1 and 3.4 percent of the respective sample mean nonemployment rates. The Wave IV coefficient is significant at the 10 percent level, while the Wave V coefficient is significant at the 5 percent level.

A.2.4 Racial Friendship Gaps and Unemployment Gaps across States

Let $\Delta F_s = \overline{F}_{w,s} - \overline{F}_{b,s}$ be the White–Black friendship gap from the November 2008 CPS. For each labor market outcome, we estimate

$$G_{x,s} = a_x + b_x \Delta F_s + X_s' \gamma_x + \varepsilon_{x,s}. \tag{24}$$

The outcomes are $G_{u,s} = 100 \times (\overline{u}_{w,s} - \overline{u}_{b,s})$, the unemployment rate gap in percentage points, and $G_{d,s} = \overline{d}_{w,s} - \overline{d}_{b,s}$, the duration gap in weeks. Unemployment rates come from the 2008–2018 ACS and duration from the 2008-2018 CPS. Controls are state population, the college-educated share, the Black share of the Black–White labor force, and average

Table A.4: FRIENDS AND LABOR MARKET OUTCOMES: ADD HEALTH

Panel A: Wave IV

	Non-employed		
	(1)	(2)	(3)
Num. friends	-0.005***	-0.003**	-0.002*
	(0.001)	(0.001)	(0.001)
Baseline controls	No	Yes	Yes
Big5 traits	No	No	Yes
School FE	Yes	Yes	Yes
Observations	9,409	9,409	9,367

Panel B: Wave V

	Non-employed		
	(1)	(2)	(3)
Num. friends	-0.014***	-0.008***	-0.006**
	(0.003)	(0.002)	(0.003)
Baseline controls	No	Yes	Yes
Big5 traits	No	No	Yes
School FE	Yes	Yes	Yes
Observations	5,827	5,827	5,799

SOURCE: Add Health Waves IV and V.
NOTES: Friendship counts and outcomes are measured in the same adult wave. Outcomes is a nonemployment indicator. All columns include school fixed effects. Columns (2) adds age, gender, race, and education; columns (3) also includes the Big Five traits. The estimated coefficients are expressed in probability units. Parentheses contain school-clustered standard errors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

hourly wages.

The coefficients in Table A.5, -1.005 and -2.146, correspond to the fitted lines in Figure 1. With controls, the coefficients are -0.743 (standard error 0.336) and -1.838 (standard error 1.016). Thus, a one-friend larger White-Black friendship gap is associated with a 0.74-percentage-point wider Black unemployment disadvantage and 1.84 additional weeks of unemployment for Black relative to White workers. The coefficient for unemployment duration is significant at the 10 percent level, compared with 5 percent for the unemployment rate coefficient.

Comparing states whose friendship gaps differ by two friends implies a 1.49-percentage-point difference in the Black unemployment disadvantage and 3.68 weeks in relative un-

employment duration, holding controls fixed.

Table A.5: RACIAL FRIENDSHIP GAPS AND UNEMPLOYMENT GAPS

	Unemployment Rate		Unemployment Duration	
	(1)	(2)	(3)	(4)
Gap in Friends	-1.005**	-0.743**	-2.146**	-1.838*
	(0.429)	(0.336)	(1.058)	(1.016)
Controls	No	Yes	No	Yes
Observations	42	42	42	42

SOURCES: November 2008 CPS friendship counts; 2008–2018 ACS unemployment rates and CPS duration.
NOTES: Each column reports the coefficient on the White-Black friendship gap for a regression at the state level. Outcomes are White-Black unemployment rate gaps in percentage points (1-2) and duration gaps in weeks (3-4). Columns (2) and (4) control for the college-educated share, the Black share of the Black–White labor force, and average hourly wages. Negative coefficients indicate a wider Black disadvantage as the White friendship advantage increases. Heteroskedasticity-robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

A.2.5 Residential Segregation and Friendship Gaps: OLS and IV Evidence

We estimate equation (1) from Section 2.4, with and without the state-level controls used in Appendix A.2.4. Residential segregation may respond to friendship patterns, and omitted state characteristics or selective migration may influence both. We therefore also instrument D_s with historical government density, Z_s, defined in Equation (23).

Historical fragmentation and instrument relevance. Our instrument adapts the approach of Cutler and Glaeser (1997). Their argument is that additional municipal jurisdictions permit greater variation in local taxes, generating fragmentation in public services and creating incentives for residential sorting. They focus on municipal and township governments because these counts are more stable than school and special districts. They report a correlation above 0.98 between metropolitan counts in 1962 and 1987. Using the earlier counts also reduces the concern that contemporary outcomes determine government organization.

Specification and identifying assumption. The first stage is

$$D_s = \pi_0 + \pi_1 Z_s + X_s' \pi_X + \nu_s. \tag{25}$$

Beyond relevance, identification requires

$$\mathbb{E}[\widetilde{Z}_s \varepsilon_s] = 0,$$

where $\widetilde{Z}_s$ is historical government density residualized on the included controls and intercept, and ε_s is the error in the friendship-gap equation.

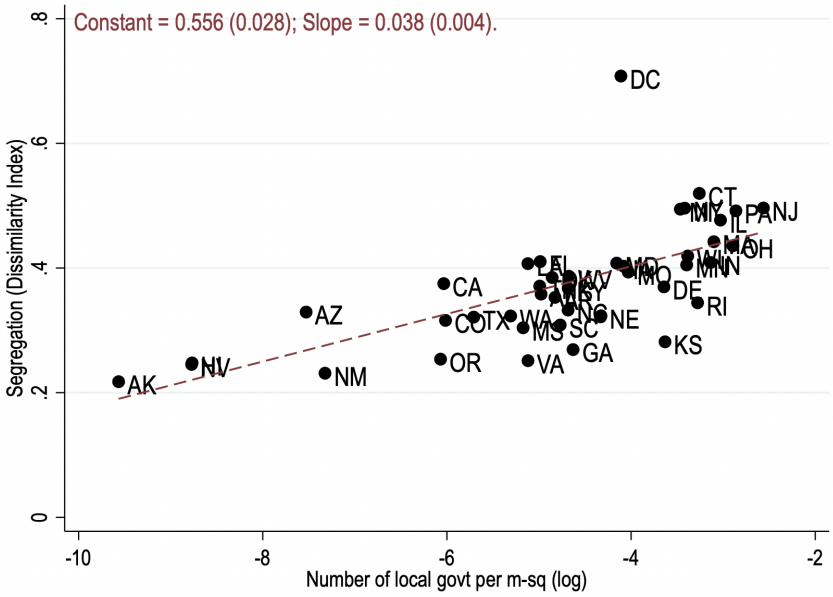
Economically, historical fragmentation must affect the racial friendship gap only through measured residential segregation, conditional on the controls. The restriction would fail, for example, if persistent jurisdictional boundaries changed school attendance, public services, or opportunities for social contact in ways not captured by D_s.

Results and magnitudes. Figure A.1 shows the first stage estimates without controls. Table A.6 reports OLS estimates in columns (1)-(2), first stages in (3)-(4), and IV estimates in (5)–(6). The first-stage coefficients are 0.038 (standard error 0.004) without controls and 0.034 (standard error 0.005) with controls; the reported F-statistics are 73.70 and 48.67.

The OLS coefficients on D_s are 3.736 (standard error 0.902) without controls and 3.618 (standard error 1.579) with controls. The corresponding IV estimates are 4.475 (standard error 1.587) and 3.792 (standard error 1.985). Without controls, a 0.1 increase in dissimilarity is therefore associated with a 0.37-friend larger gap under OLS; the IV implies an estimated increase of 0.45 friends. With controls, the corresponding magnitudes are 0.36 and 0.38 friends. The point estimates are similar, although the IV estimate with controls is slightly less precise.

Figure A.2 and Table A.7 show the results are robust to a state-level dissimilarity index. Instead of computing the dissimilarity index by county and averaging over the state, this

Figure A.1: FIRST STAGE: RESIDENTIAL SEGREGATION AND HISTORICAL GOVERNMENT FRAGMENTATION



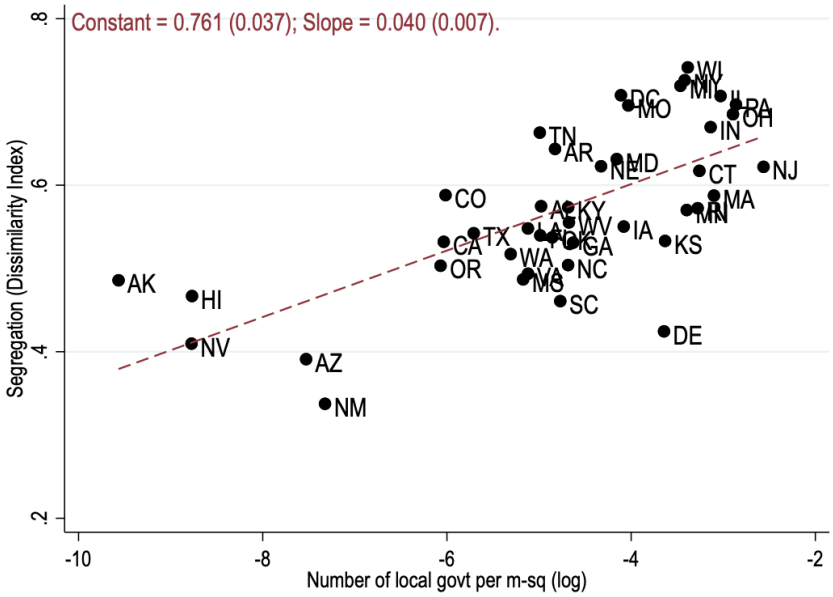
SOURCES: 2010 Census tract counts from NHGIS and the 1962 Census of Governments.
NOTES: Each point is one of the 42 state-level markets. The vertical axis is the population-weighted county dissimilarity measure D_s; the horizontal axis is log municipal and township density Z_s. The line is the OLS fit without controls; annotations report its intercept and slope, with heteroskedasticity-robust standard errors in parentheses.

Table A.6: HISTORICAL GOVERNMENT FRAGMENTATION, SEGREGATION, AND THE FRIENDSHIP GAP

			IV			
	OLS		First stage: D_s		Second stage: ΔN_s	
	(1)	(2)	(3)	(4)	(5)	(6)
Log local-government density, 1962			0.038***	0.034***		
			(0.004)	(0.005)		
Dissimilarity index, D_s	3.736***	3.618**			4.475***	3.792*
	(0.902)	(1.579)			(1.587)	(1.985)
Observations	42	42	42	42	42	42
First stage F-statistic			73.70	48.67		
Controls	No	Yes	No	Yes	No	Yes

SOURCES: November 2008 CPS, 2010 Census tract counts from NHGIS, and the 1962 Census of Governments.
NOTES: Columns (1)-(2) report OLS estimates of (1); (3)-(4) report first stages for D_s; and (5)-(6) report 2SLS estimates using Z_s. The table's ΔN_s is the White-Black friendship gap ΔF_s. Even-numbered columns add state population, college share, Black labor-force share, and mean hourly wages. Parentheses contain heteroskedasticity-robust standard errors; F-statistics refer to the excluded instrument in the first stage. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Figure A.2: FIRST STAGE: RESIDENTIAL SEGREGATION AND HISTORICAL GOVERNMENT FRAGMENTATION - ROBUSTNESS



SOURCES: 2010 Census tract counts from NHGIS and the 1962 Census of Governments.
NOTES: Each point is one of the 42 state-level markets. The vertical axis is the dissimilarity measure $\tilde{D}_s$. The horizontal axis is log municipal and township density Z_s. The line is the OLS fit without controls, annotations report its intercept and slope, with heteroskedasticity-robust standard errors in parentheses.

Table A.7: HISTORICAL GOVERNMENT FRAGMENTATION, SEGREGATION, AND THE FRIENDSHIP GAP - ROBUSTNESS

			IV			
	OLS		First stage: $\tilde{D}_s$		Second stage: ΔN_s	
	(1)	(2)	(3)	(4)	(5)	(6)
Log local-government density, 1962			0.040***	0.035***		
			(0.007)	(0.008)		
Dissimilarity index, D_s	3.246**	2.680*			4.283**	3.610*
	(1.370)	(1.575)			(1.684)	(2.020)
Observations	42	42	42	42	42	42
First stage F-statistic			29.38	20.81		
Controls	No	Yes	No	Yes	No	Yes

SOURCES: November 2008 CPS, 2010 Census tract counts from NHGIS, and the 1962 Census of Governments.
NOTES: Columns (1)-(2) report OLS estimates of (1); (3)-(4) report first stages for D_s; and (5)-(6) report 2SLS estimates using Z_s. The table's ΔN_s is the White-Black friendship gap ΔF_s. Even-numbered columns add state population, college share, Black labor-force share, and mean hourly wages. Parentheses contain heteroskedasticity-robust standard errors; F-statistics refer to the excluded instrument in the first stage. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

alternative measure computes for the entire state:

$$\tilde{D}_s = \frac{1}{2} \sum_{j \in s} \left| \frac{B_j}{B_s} - \frac{W_j}{W_s} \right|$$

where s and j index state and tracts within the state, respectively.

A.2.6 Segregation within School Friendship Networks in AddHealth

Panel B of Figure 2 relates school friendship-network segregation to the White-Black gap in mean received nominations. The fitted slope is 3.804 (standard error 0.921), so a 0.1 increase in the index is associated with a 0.38-nomination larger gap. The coefficient is significant at the 1 percent level. Both variables describe the same school network.

B Quantitative Exercise

This appendix provides the definition of stationary equilibrium (Appendix B.1), and details on the calibration strategy used in Section 4. Appendix B.2 defines the empirical inputs and their sources. Appendix B.3 explains how these inputs determine the model parameters. Appendix B.4 discusses the estimates and compares the model with its targets. Appendix C.1 explains how we average state-level outcomes, calculate changes in racial gaps, and measure welfare.

B.1 Stationary Equilibrium

Given (μ_b, D), meeting and dissolution parameters $(\bar{\eta}_{bb}, \bar{\eta}_{ww}, \bar{\eta}_x, \zeta, \lambda)$, labor market primitives $(y_r, b_r, \delta_r, \alpha_r)_{r\in\{b,w\}}$, effort-cost parameters (ν_b, ν_w), and (β, c, χ), a stationary symmetric mean-field equilibrium consists of

$$\{e_{rg}, N_{rg}, \Lambda_g, p_g, \pi_g, P_r, h_r, u_r, w_r, J_r, W_r, U_r, q_r\}_{r,g\in\{b,w\}} \quad \text{and} \quad (V, v, \theta, q)$$

such that:

1. Workers solve the stationary networking problem in Section 3.5, taking aggregate conditions as given. Aggregate efforts are $E_{rg} = \mu_r e_{rg}$, and cross-race effort ratios satisfy (3).

2. Friendship counts have their stationary Poisson distributions, with means $N_{rg} = a_{rg} e_{rg}$ and cross-race link balance $\mu_b N_{bw} = \mu_w N_{wb}$.

3. Referral and job finding probabilities satisfy (6)-(10); unemployment satisfies (13); and matching and vacancy-filling probabilities satisfy (11)-(12), with $\theta = v/u$.

4. Values and wages satisfy (14)-(18).

5. Vacancies satisfy free entry, $V = 0$, which implies

$$c = \beta \sum_{r\in\{b,w\}} q_r \frac{y_r - w_r}{1 - \beta(1 - \delta_r)}. \tag{B.1}$$

B.2 Data Moments for Calibration

We calibrate 42 state-level labor markets, including the District of Columbia. Labor market inputs use the 2008-2018 American Community Survey (ACS; Ruggles et al., 2025) and Current Population Survey (CPS; Flood et al., 2025). Friendship counts come from the November 2008 CPS. The sample consists of Black and White labor-force participants aged 25-55 in states where Black workers account for at least 1 percent of the Black-White labor force. Appendix A.1 documents further details on the underlying samples and variables. Below, s indexes states, $r \in \{b, w\}$ indexes race, and hats distinguish empirical inputs or targets from model outcomes.

Racial shares of the labor force. The input $\widehat{\mu}_{b,s}$ is the number of Black labor-force participants in state s divided by the total number of Black and White labor-force participants in that state. We calculate both counts from the pooled ACS data using person weights (`PERWT`) and set $\widehat{\mu}_{w,s} = 1 - \widehat{\mu}_{b,s}$. Figure B.1 reports $\widehat{\mu}_{b,s}$.

Unemployment rates. For each state and race, $\widehat{u}_{r,s}$ is the ACS person-weighted number of unemployed respondents divided by the corresponding labor force. Employment status is determined by `EMPSTAT`. Figure B.3 reports $100 \times \widehat{u}_{r,s}$, in percent.

Residual hourly wages. The wage targets also come from the pooled ACS. We retain wage and salary workers with positive wage income and annual hours, excluding the self-employed. Hourly wages equal annual wage-and-salary income (`INCWAGE`) divided by weeks worked times usual weekly hours (`UHRSWORK`). When weeks worked are reported in intervals (`WKSWORK2`), we use their midpoints, as described in Appendix A.1.1. We residualized wages with respect to calendar year, gender, college education, industry, occupation, and age. The target $\widehat{w}_{r,s}$ is the residual mean for race r in state s, divided by the national residual mean for White workers. Figure B.2 shows normalized residual wage levels.

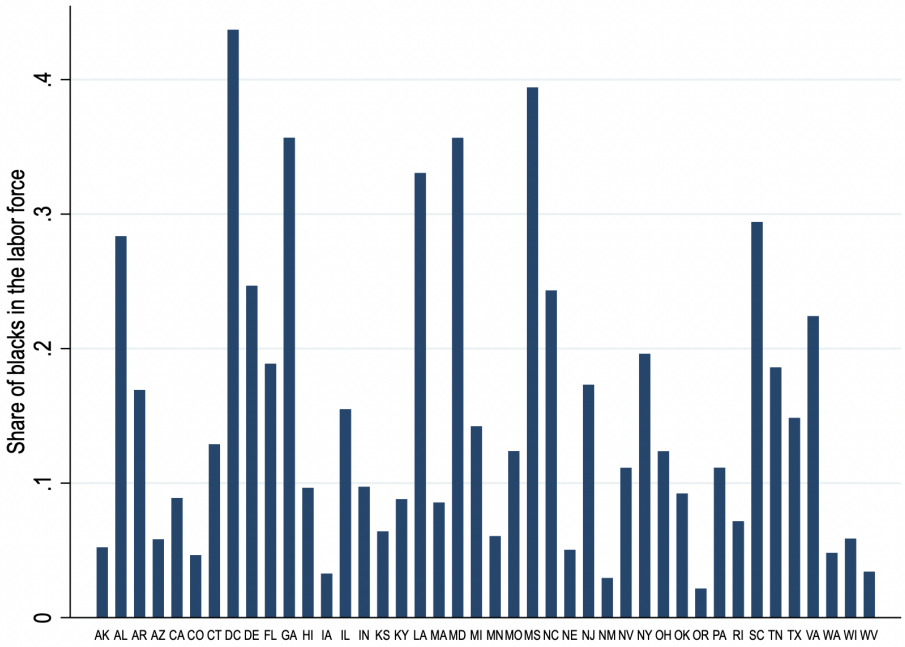
Unemployment duration. The target $\widehat{dur}_s$ is the CPS-weighted mean of DURUNEMP, in weeks, among Black and White unemployed respondents in state s over 2008-2018. Figure B.4 reports this target.

Residential segregation. We construct $\widehat{D}_s$ from 2010 Census tract counts obtained through NHGIS. It is a population-weighted average of county-level Black-White dissimilarity indices and therefore measures residential sorting across tracts within counties. Appendix A.1.4 gives the formula and geographic restrictions. In each state economy, we set the model's cross-race formation-friction index to $D_s = \widehat{D}_s$.

Friendship counts and their relationship with segregation. We use two pooled mean friendship counts from the November 2008 CPS, $\widehat{N}_w$ and $\widehat{N}_b$, calculated with survey weights. We also target the intercept $\widehat{\beta}_0$ and slope $\widehat{\beta}_1$ from regressing the White-Black state friendship gap on $\widehat{D}_s$ without controls, as reported in Section 2.4. Together, these four moments describe the level of friendships by race and how the racial gap varies with segregation. Table B.3 reports the targets used in the current calibration.

Share of hires obtained through referrals. We set $\widehat{\text{ref}} = 0.50$ in every state. This choice is based on the evidence reviewed in Ioannides and Datcher Loury (2004, p. 1058).

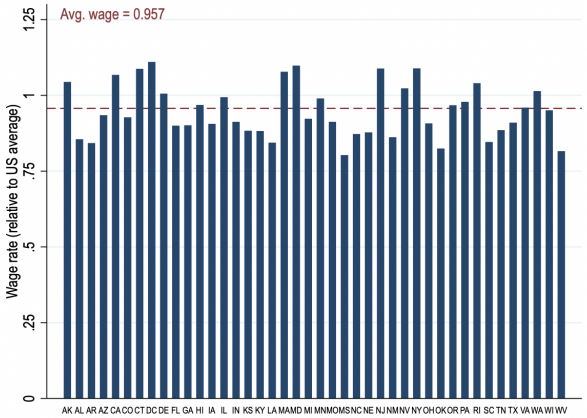
Figure B.1: BLACK SHARE OF THE BLACK–WHITE LABOR FORCE, BY STATE



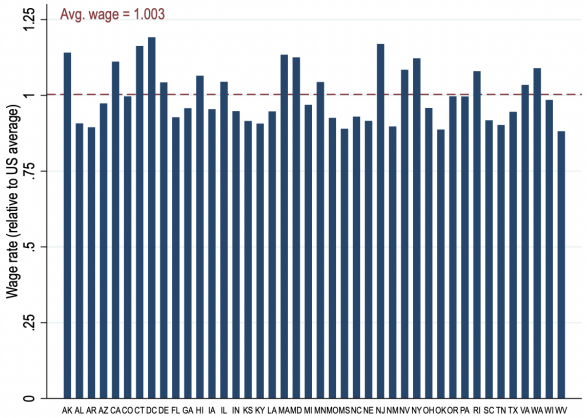
SOURCE: Authors' calculations using the 2008–2018 ACS.
NOTES: Bars report the Black share of the Black–White labor force among respondents aged 25–55.

Figure B.2: RESIDUAL HOURLY WAGES, BY STATE AND RACE

(A) Black workers



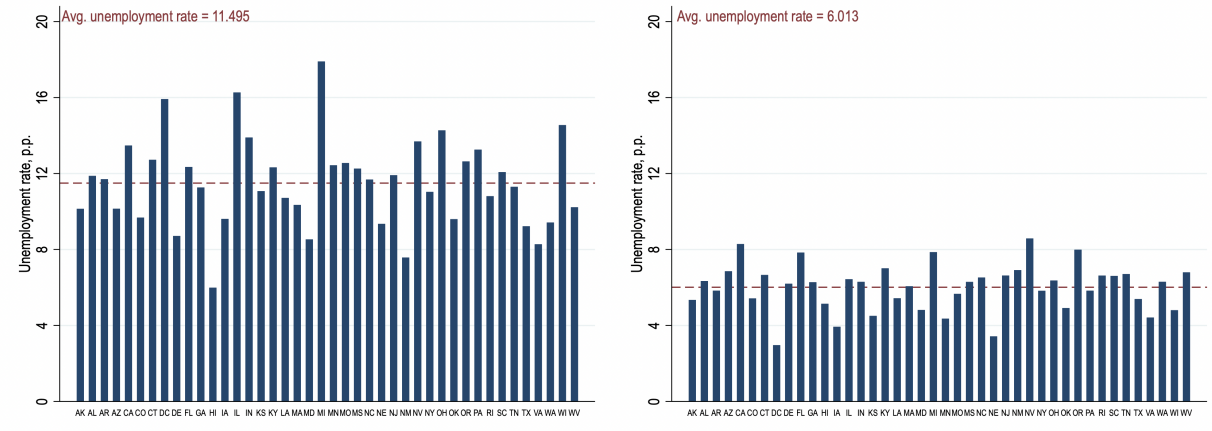
(B) White workers



SOURCE: Authors' calculations using the 2008–2018 ACS.
NOTES: Bars report residual mean hourly wage targets for Black (A) and White (B) wage and salary workers aged 25–55. Controls include dummies for year, gender, college education, industry, occupation, and age. Both panels divide residual wages by the same national residual mean for White workers. Dashed lines show the corresponding pooled sample means.

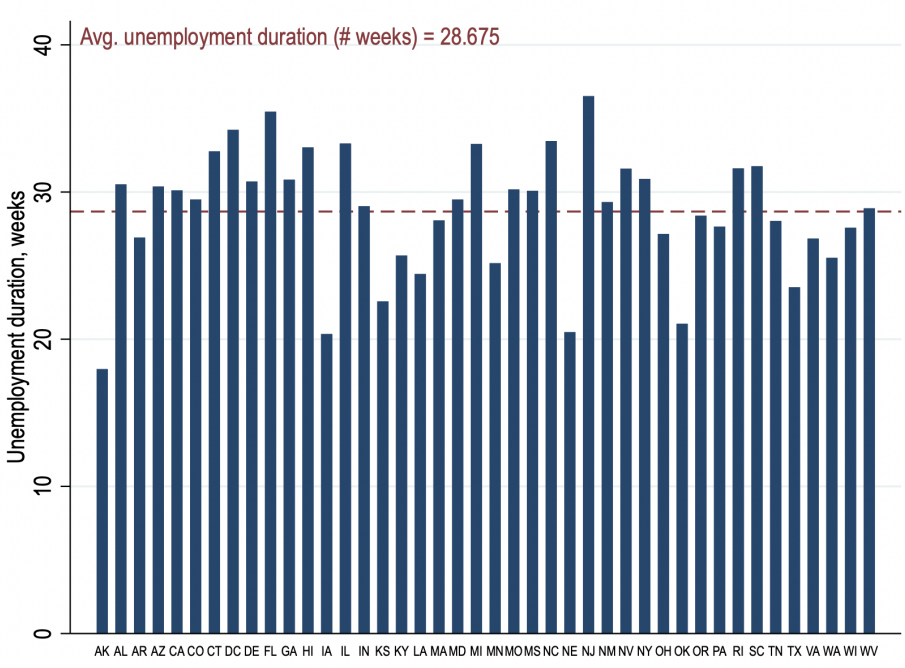
Figure B.3: UNEMPLOYMENT RATES, BY STATE AND RACE

(A) Black workers **(B)** White workers



SOURCE: Authors' calculations using the 2008–2018 ACS.
NOTES: Bars report unemployment as a percentage of the corresponding race's labor force among respondents aged 25–55 in the calibrated markets. Panel A reports Black workers and panel B White workers. Dashed lines show the pooled sample unemployment rate for each race.

Figure B.4: UNEMPLOYMENT DURATION, BY STATE



SOURCE: Authors' calculations using the 2008–2018 CPS.
NOTES: Bars report the survey-weighted mean elapsed duration of ongoing unemployment spells, in weeks, among Black and White unemployed respondents aged 25-55 in each calibrated market. The dashed line shows the pooled sample mean.

Table B.1: CALIBRATION STRATEGY

Parameter or input	Value or empirical target	Source or model condition
Observed state characteristics		
$\mu_{b,s}$	Black share of the Black–White labor force	2008–2018 ACS
D_s	Population-weighted county dissimilarity	2010 Census via NHGIS
Assigned parameters		
β	0.997; 4 percent annual interest	Assigned
α_b, α_w	0.5; equal bargaining weights	Assumed
κ	0.40; $b_{r,s} = \kappa \widehat{w}_{r,s}$	Hall (2005); Hornstein et al. (2011)
ν_b, ν_w	1; quadratic effort costs	Assumed
λ	0.0087; 48 percent survival over 84 months	Mollenhorst et al. (2014); see text
State-specific parameters		
χ_s; implied v_s	Pooled duration; 0.50 referral share	2008–2018 CPS; Ioannides and Datcher Loury (2004)
$\delta_{b,s}, \delta_{w,s}$	Unemployment rates by race	2008–2018 ACS; (B.4)
$y_{b,s}, y_{w,s}$	Residual wage levels by race	2008–2018 ACS; (B.5)
c_s	Cost consistent with calibrated hiring and profits	Free entry; (B.6)
Common friendship-formation parameters		
$\bar{\eta}_{ww}, \bar{\eta}_{bb}, \bar{\eta}_x, \zeta$	Two mean friendship counts; friendship-gap regression intercept and slope	November 2008 CPS and 2010 Census; (B.8)

NOTES: s indexes states and $r \in \{b, w\}$ indexes race. Appendix B.2 defines the empirical targets. The text explains the assigned values and the source of the survival benchmark. Equations (B.2)–(B.3) jointly determine v_s and χ_s for given networks. Vacancy supply is an equilibrium outcome and is not held fixed in the counterfactual. Tables B.2 and B.3 report estimates and the comparison with friendship targets.

B.3 Calibration Strategy

We first assign the parameters that are common across states. We then use state-level labor market targets to determine separation probabilities, productivity, referral effectiveness, and vacancy costs. Four common friendship-formation parameters are chosen to match the friendship moments. Table B.1 summarizes the values, targets, and sources.

Job finding and referrals. Let $\widehat{u}_s = \sum_r \widehat{\mu}_{r,s} \widehat{u}_{r,s}$, using the ACS racial shares and unemployment rates. For given networks and a candidate vacancy supply v_s, Section 3.3 gives the probability $P_{r,s}$ that an unemployed worker receives at least one referral. This prob-

ability depends on v_s, because employed friends must first receive a vacancy lead. The job finding probability is $h_{r,s} = v_s + \chi_s(1 - v_s)P_{r,s}$. We choose (v_s, χ_s) to match the CPS duration target and the assigned referral share of 0.50.

With a constant monthly job finding probability, a model unemployment spell has mean length $1/h_{r,s}$ months. The calibration uses this reciprocal probability as the counterpart of reported duration. Converting months to weeks with $\tau = 52/12$ and weighting by each race's share of the unemployed gives

$$\widehat{dur}_s = \tau \sum_{r \in \{b,w\}} \frac{\widehat{\mu}_{r,s}\widehat{u}_{r,s}}{\widehat{u}_s} \frac{1}{h_{r,s}}. \tag{B.2}$$

The left-hand side is the pooled CPS mean. On the right-hand side, $\widehat{\mu}_{r,s}\widehat{u}_{r,s}/\widehat{u}_s$ is race r's share of unemployment implied by the ACS targets. Longer target durations require lower job finding probabilities, other things equal.

The model share of new matches obtained through referrals satisfies

$$\widehat{\text{ref}} = \frac{\sum_r \widehat{\mu}_{r,s}\widehat{u}_{r,s}\chi_s(1 - v_s)P_{r,s}}{\sum_r \widehat{\mu}_{r,s}\widehat{u}_{r,s}h_{r,s}}. \tag{B.3}$$

The numerator is the mass of unemployed workers who receive no direct lead but find a job through referrals. The denominator is the mass of all new matches. Thus, the duration target determines the overall pace of job finding, while the referral target determines the relative contribution of the two hiring channels. Equations (B.2) and (B.3) are solved together, recalculating $P_{r,s}$ as v_s changes.

Job separations. Given $h_{r,s}$, we choose each race's monthly separation probability to reproduce its ACS unemployment rate. Stationary employment-flow balance, $(1 - \widehat{u}_{r,s})\delta_{r,s} = \widehat{u}_{r,s}h_{r,s}$, implies

$$\delta_{r,s} = \frac{\widehat{u}_{r,s}}{1 - \widehat{u}_{r,s}} h_{r,s}. \tag{B.4}$$

For a given job finding probability, higher unemployment requires more frequent job loss.

Productivity. We next determine the productivity needed to support each residual ACS wage target under Nash bargaining. Let $A_{r,s} = 1 - \beta(1 - \delta_{r,s})$. With $V = 0$, the worker's employment surplus is $(\widehat{w}_{r,s} - b_{r,s})/(A_{r,s} + \beta h_{r,s})$, and the firm's surplus is $(y_{r,s} - \widehat{w}_{r,s})/A_{r,s}$. Dividing these surpluses according to the worker bargaining weight α_r gives

$$y_{r,s} = \widehat{w}_{r,s} + \frac{1 - \alpha_r}{\alpha_r} \frac{A_{r,s}}{A_{r,s} + \beta h_{r,s}} (\widehat{w}_{r,s} - b_{r,s}). \tag{B.5}$$

Productivity exceeds the wage by the flow profit required to deliver the firm's share of the match surplus. The calculation uses the assigned $b_{r,s}$ and α_r, together with calibrated separation and job finding probabilities.

Vacancy costs. Free entry equates the monthly cost of an open vacancy to its expected discounted value from being filled. A vacancy is filled by race r with probability $\widehat{\mu}_{r,s}\widehat{u}_{r,s}h_{r,s}/v_s$, and the value of that filled job is $(y_{r,s} - \widehat{w}_{r,s})/A_{r,s}$. Hence,

$$c_s = \beta \sum_r \frac{\widehat{\mu}_{r,s}\widehat{u}_{r,s}h_{r,s}}{v_s} \frac{y_{r,s} - \widehat{w}_{r,s}}{A_{r,s}}. \tag{B.6}$$

Friendship formation. Write $\vartheta = (\bar{\eta}_{ww}, \bar{\eta}_{bb}, \bar{\eta}_x, \zeta)$ and $N_{r,s} = N_{rb,s} + N_{rw,s}$. For a candidate ϑ, we solve the state-level calibration conditions jointly with workers' networking choices and stationary friendship formation. The resulting mean friendship counts depend on both meeting opportunities and their labor market returns. We then estimate the model counterpart of the empirical regression:

$$N_{w,s} - N_{b,s} = \beta_0^{\text{mod}} + \beta_1^{\text{mod}} \widehat{D}_s + \varepsilon_s^{\text{mod}}. \tag{B.7}$$

We use the same states, weights, and specification without controls as in Section 2.4. Let $\overline{N}_r(\vartheta)$ be the model mean calculated with the weights used for the corresponding CPS racial mean. We compare the four model moments with the four targets:

$$\begin{aligned} m(\vartheta) &= \left(\overline{N}_w(\vartheta), \overline{N}_b(\vartheta), \beta_0^{\text{mod}}(\vartheta), \beta_1^{\text{mod}}(\vartheta)\right)', \\ \widehat{m} &= (\widehat{N}_w, \widehat{N}_b, \widehat{\beta}_0, \widehat{\beta}_1)'. \end{aligned}$$

The parameter vector minimizes

$$\min_{\vartheta} [m(\vartheta) - \widehat{m}]' \mathcal{A} [m(\vartheta) - \widehat{m}], \tag{B.8}$$

where $\mathcal{A}$ is the identity matrix. The two same-race efficiencies help determine friendship levels, while $\bar{\eta}_x$ and ζ govern cross-race formation and its sensitivity to segregation.

B.4 Calibrated Parameters and Estimation Fit

Table B.2 reports state-specific labor market parameters and assigned unemployment incomes. Table B.3 reports the common formation parameters and compares the model with the friendship moments used in estimation.

State-specific parameters. Monthly separation probabilities range from 0.45 to 1.31 percent for White workers and from 0.76 to 2.88 percent for Black workers. The Black separation probability is higher in every calibrated market.

Referral effectiveness χ_s ranges from 0.2872 in Nevada to 0.3964 in DC. The parameter varies despite the common 0.50 referral-share target: different networks and vacancy supplies require different conditional success probabilities to reproduce that target. Vacancy costs range from 0.1877 in Nebraska to 0.8115 in New Jersey, in model-based income units per vacancy and month.

Productivity ranges from 0.9203 to 1.2307 for White workers and from 0.8705 to 1.2278 for Black workers. These levels support the residual wage targets under the assigned bargaining weights and unemployment incomes.

Table B.2: STATE-LEVEL LABOR MARKET PARAMETERS

State	y_w	y_b	b_w	b_b	δ_w	δ_b	c	χ
AL	0.9515	0.9258	0.3630	0.3421	0.0101	0.0164	0.5470	0.3521
AK	1.1856	1.1134	0.4564	0.4176	0.0131	0.0288	0.3027	0.3446
AZ	1.0240	1.0022	0.3893	0.3737	0.0103	0.0136	0.5401	0.3062
AR	0.9344	0.9099	0.3578	0.3369	0.0101	0.0182	0.4195	0.3514
CA	1.1780	1.1655	0.4445	0.4269	0.0129	0.0184	0.7428	0.3001
CO	1.0398	0.9916	0.3986	0.3709	0.0082	0.0137	0.4340	0.3109
CT	1.2229	1.1839	0.4652	0.4349	0.0096	0.0156	0.7196	0.2998
DE	1.0927	1.0707	0.4171	0.4023	0.0096	0.0113	0.5624	0.3238
DC	1.2265	1.2278	0.4767	0.4440	0.0045	0.0222	0.8065	0.3964
FL	0.9823	0.9785	0.3710	0.3599	0.0106	0.0142	0.7203	0.3193
GA	1.0035	0.9721	0.3829	0.3605	0.0098	0.0160	0.5906	0.3321
HI	1.1109	1.0155	0.4259	0.3872	0.0069	0.0076	0.4818	0.2899
IL	1.0971	1.1026	0.4179	0.3976	0.0093	0.0206	0.6907	0.3230
IN	0.9932	0.9983	0.3790	0.3650	0.0101	0.0198	0.4974	0.3283
IA	0.9841	0.9655	0.3816	0.3624	0.0085	0.0194	0.2148	0.3789
KS	0.9479	0.9484	0.3661	0.3532	0.0088	0.0227	0.2696	0.3551
KY	0.9531	0.9561	0.3626	0.3529	0.0126	0.0198	0.4496	0.3366
LA	0.9858	0.9058	0.3788	0.3375	0.0109	0.0184	0.4072	0.3896
MD	1.1691	1.1667	0.4500	0.4391	0.0079	0.0120	0.5267	0.3468
MA	1.1870	1.1567	0.4536	0.4310	0.0099	0.0145	0.5327	0.3079
MI	1.0253	1.0325	0.3875	0.3691	0.0115	0.0227	0.7397	0.3261
MN	1.0810	1.0725	0.4175	0.3958	0.0078	0.0207	0.3354	0.3407
MS	0.9321	0.8705	0.3558	0.3212	0.0104	0.0178	0.5550	0.3659
MO	0.9670	0.9917	0.3702	0.3651	0.0087	0.0173	0.4713	0.3333
NE	0.9418	0.9334	0.3662	0.3510	0.0073	0.0201	0.1877	0.3910
NV	1.1520	1.1175	0.4337	0.4092	0.0126	0.0204	0.7875	0.2872
NJ	1.2307	1.1816	0.4678	0.4354	0.0087	0.0131	0.8115	0.2963
NM	0.9441	0.9099	0.3589	0.3447	0.0106	0.0121	0.4751	0.3099
NY	1.1735	1.1740	0.4488	0.4356	0.0089	0.0145	0.6095	0.3196
NC	0.9769	0.9443	0.3719	0.3489	0.0094	0.0146	0.6064	0.3302
OH	1.0040	0.9940	0.3833	0.3629	0.0110	0.0219	0.4863	0.3401
OK	0.9203	0.8788	0.3549	0.3298	0.0106	0.0184	0.2625	0.3790
OR	1.0544	1.0493	0.3986	0.3869	0.0128	0.0218	0.5891	0.3026
PA	1.0409	1.0664	0.3985	0.3914	0.0098	0.0197	0.4744	0.3336
RI	1.1346	1.1202	0.4318	0.4160	0.0096	0.0140	0.6121	0.2955
SC	0.9640	0.9169	0.3670	0.3383	0.0101	0.0163	0.5903	0.3399
TN	0.9472	0.9544	0.3608	0.3540	0.0113	0.0166	0.4912	0.3426
TX	0.9842	0.9684	0.3782	0.3639	0.0105	0.0163	0.3466	0.3524
VA	1.0725	1.0164	0.4139	0.3837	0.0074	0.0135	0.3784	0.3239
WA	1.1408	1.0813	0.4357	0.4055	0.0112	0.0151	0.4692	0.3117
WV	0.9265	0.8752	0.3525	0.3262	0.0107	0.0138	0.4575	0.3208
WI	1.0232	1.0428	0.3939	0.3802	0.0079	0.0223	0.3818	0.3344

NOTES: Each row is one of the 42 calibrated markets, including DC. y_w, y_b are model productivity levels; b_w, b_b are assigned unemployment incomes, $b_{r,s} = 0.4\widehat{w}_{r,s}$; and δ_w, δ_b are monthly separation probabilities, reported as fractions. c is the monthly cost per vacancy, and χ is referral effectiveness conditional on receiving referrals and no direct lead.

Table B.3: COMMON FRIENDSHIP-FORMATION PARAMETERS AND TARGETED FIT

Parameter	Estimate	Target moment	Data	Model
$\bar{\eta}_{ww}$	0.2493	Mean white degree	5.1700	5.2522
$\bar{\eta}_{bb}$	0.1444	Mean black degree	3.7800	3.6948
$\bar{\eta}_x$	1.8765	Friend gap on D: intercept	-0.0782	-0.1593
ζ	8.5023	Friend gap on D: slope	3.7355	3.7009

NOTES: The four parameters are common across states and estimated jointly. $\bar{\eta}_{ww}, \bar{\eta}_{bb}$ govern same-race formation; $\bar{\eta}_x$ is cross-race efficiency at $D = 0$; and ζ determines its sensitivity in $\eta_x(D) = \bar{\eta}_x \exp(-\zeta D)$. Degree means number of friends. Data and model columns report pooled racial friendship means and the intercept and slope of the White-Black friendship-gap regression without controls.

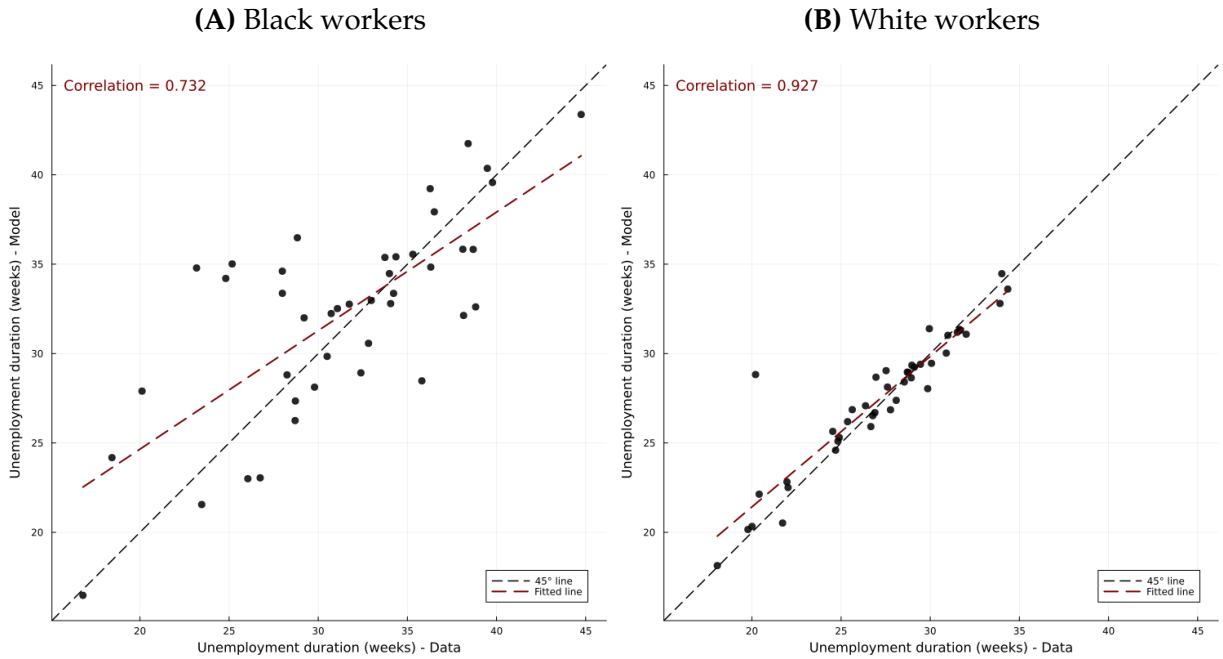
Friendship-formation parameters. The estimates are $\bar{\eta}_{ww} = 0.2493$, $\bar{\eta}_{bb} = 0.1444$, $\bar{\eta}_x = 1.8765$, and $\zeta = 8.5023$. At the same effort, the same-race technology produces about 1.73 times as many new friendships for White workers as for Black workers.

The parameter $\bar{\eta}_x$ measures cross-race meeting efficiency at $D = 0$, before accounting for effort from the other group. With the estimated ζ, a 0.1 increase in D multiplies this efficiency by $\exp(-0.1 \times 8.5023) \simeq 0.427$, a decline of about 57 percent.

Comparison with the targets. The model produces mean friendship counts of 5.2522 for White workers and 3.6948 for Black workers, compared with the calibration targets of 5.1700 and 3.7800. The model regression slope is 3.7009, compared with 3.7355 in the data; its intercept is -0.1593, compared with -0.0782. The means and slope are close to their targets, while the intercept differs by about 0.08 friends.

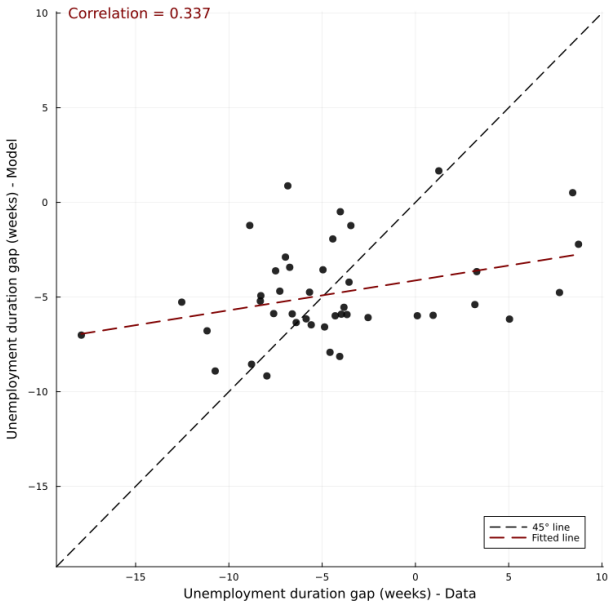
Untargeted moments. Figure B.5 compares observed and predicted unemployment duration across states for Black workers (Panel A) and White workers (Panel B). The dashed line is the fitted line. Figure B.6 compares observed and predicted racial unemployment duration gap across states. In both figures, the black dashed lines are the 45 degree lines, while the red dashed lines are fitted lines. Despite not being targeted, the model reproduces almost the same observed unemployment duration of White and Black workers across US states: the correlations between model and data are 0.93 and 0.73 respectively. On the other hand, the same correlation for racial unemployment duration gap across US states is 0.34.

Figure B.5: UNTARGETED MOMENTS: UNEMPLOYMENT DURATION BY STATE AND RACE



NOTES: Each dot is a state comparing simulated against observed unemployment duration among Black workers (Panel A) and White workers (Panel B). The black dashed lines are the 45 degree lines; the red dashed lines are fitted lines.

Figure B.6: UNTARGETED MOMENTS: UNEMPLOYMENT DURATION GAP BY STATE



NOTES: Each dot is a state comparing simulated against observed racial unemployment duration gap. The black dashed lines are the 45 degree lines; the red dashed lines are fitted lines.

C Counterfactual Outcomes

C.1 Definitions and Aggregation

This subsection explains how we average state-level outcomes, calculate changes in racial gaps, and measure welfare.

Averages across states. Let $\mathcal{S}$ be the set of calibrated markets and P_s the population in state s, taken from the NHGIS (Appendix A.1.4). For each race, we calculate

$$\overline{x}_r = \sum_{s \in \mathcal{S}} \frac{P_s \mu_{r,s}}{\sum_{s' \in \mathcal{S}} P_j \mu_{r,j}} x_{r,s}. \tag{C.1}$$

These weights are held fixed between the baseline and counterfactual.

Changes and racial gaps. Superscripts 0 and 1 denote the baseline and counterfactual. In Tables 2, C.6, and C.3 changes in friendship counts and duration are $\overline{x}_r^1 - \overline{x}_r^0$, in numbers of friends and weeks. Changes in unemployment are $100 \times (\overline{u}_r^1 - \overline{u}_r^0)$, in percentage points. Changes in wages and the two welfare measures are percentage changes, $100 \times (\overline{x}_r^1 / \overline{x}_r^0 - 1)$, calculated after averaging state-level outcomes.

Panels A-D of Figure 3 report counterfactual-minus-baseline changes in the following state-level gaps:

$$\text{A: } N_{w,s} - N_{b,s}, \quad \text{B: } dur_{b,s} - dur_{w,s}, \quad \text{C: } 100 \times (u_{b,s} - u_{w,s}), \quad \text{D: } 100 \times (\ln w_{w,s} - \ln w_{b,s}).$$

Panel A is measured in friends, panel B in weeks, panel C in percentage points, and panel D in log points multiplied by 100.

Gross income and net welfare. The tables report both gross discounted income and welfare net of networking costs. Gross discounted income, labeled "Welfare (gross)," is

$$\mathcal{W}_{r,s}^{\text{gross}} = \frac{(1 - u_{r,s}) w_{r,s} + u_{r,s} b_{r,s}}{1 - \beta}.$$

It includes wages while employed and unemployment income while unemployed. Net welfare subtracts the per-period networking cost:

$$\mathcal{W}_{r,s} = \frac{(1 - u_{r,s})w_{r,s} + u_{r,s}b_{r,s} - C_r(e_{rb,s}, e_{rw,s})}{1 - \beta}. \tag{C.2}$$

The cost is paid in both employment states. Both measures evaluate a worker drawn from the stationary distribution of the corresponding economy and discount the resulting expected flow from the current period onward. We first calculate welfare in each state and then average using equation (C.1).

C.2 Targeting the IV Friendship-Gap Relationship

In this section, we examine whether the results depend on using OLS rather than IV estimates of the relationship between segregation and racial friendship gaps. We replace the benchmark intercept and slope with the IV targets -0.3541 and 4.4746. The slope corresponds to the specification without state-level controls in column (5) of Table A.6. Tables C.1 and C.2 report the estimates and fit. The model's fitted slope is 4.44, close to the IV target of 4.47, while mean friendship counts remain close to the CPS targets.

We then repeat the experiment in Section 4, setting $D_s = D_{\min}$ in every state, where $D_{\min}$ is the lowest observed dissimilarity in the calibrated sample. Under this parametrization, a reduction in friendship formation barriers produces larger effects. Black unemployment falls by 1.99 percentage points, duration by 6.30 weeks, and wages rise by 1.22 percent (Table C.3). The corresponding benchmark changes are 1.80 percentage points, 5.67 weeks, and 1.10 percent. Thus, replacing both regression targets with the IV estimates increases the estimated labor market gains for Black workers.

Table C.1: STATE-LEVEL PARAMETERS: IV TARGETS

State	y_w	y_b	b_w	b_b	δ_w	δ_b	c	χ
AL	0.9515	0.9259	0.3630	0.3421	0.0101	0.0164	0.5470	0.3523
AK	1.1856	1.1133	0.4564	0.4176	0.0130	0.0294	0.3027	0.3426
AZ	1.0240	1.0022	0.3893	0.3737	0.0103	0.0136	0.5401	0.3059
AR	0.9344	0.9099	0.3578	0.3369	0.0101	0.0182	0.4195	0.3514
CA	1.1780	1.1655	0.4445	0.4269	0.0129	0.0184	0.7428	0.3001
CO	1.0398	0.9916	0.3986	0.3709	0.0082	0.0138	0.4340	0.3105
CT	1.2228	1.1839	0.4652	0.4349	0.0096	0.0156	0.7196	0.3000
DE	1.0927	1.0707	0.4171	0.4023	0.0096	0.0113	0.5624	0.3240
DC	1.2265	1.2278	0.4767	0.4440	0.0045	0.0222	0.8065	0.3978
FL	0.9823	0.9785	0.3710	0.3599	0.0106	0.0141	0.7203	0.3196
GA	1.0036	0.9721	0.3829	0.3605	0.0098	0.0160	0.5906	0.3296
HI	1.1109	1.0153	0.4259	0.3872	0.0069	0.0078	0.4818	0.2882
IL	1.0971	1.1026	0.4179	0.3976	0.0093	0.0206	0.6907	0.3233
IN	0.9932	0.9984	0.3790	0.3650	0.0101	0.0198	0.4974	0.3284
IA	0.9841	0.9655	0.3816	0.3624	0.0085	0.0193	0.2148	0.3788
KS	0.9479	0.9484	0.3661	0.3532	0.0088	0.0229	0.2696	0.3538
KY	0.9531	0.9561	0.3626	0.3529	0.0126	0.0197	0.4496	0.3365
LA	0.9857	0.9058	0.3788	0.3375	0.0109	0.0184	0.4072	0.3904
MD	1.1691	1.1668	0.4500	0.4391	0.0079	0.0119	0.5267	0.3475
MA	1.1870	1.1567	0.4536	0.4310	0.0099	0.0145	0.5327	0.3079
MI	1.0253	1.0325	0.3875	0.3691	0.0115	0.0226	0.7397	0.3263
MN	1.0810	1.0726	0.4175	0.3958	0.0078	0.0206	0.3354	0.3407
MS	0.9321	0.8705	0.3558	0.3212	0.0104	0.0178	0.5550	0.3651
MO	0.9670	0.9917	0.3702	0.3651	0.0087	0.0173	0.4713	0.3334
NE	0.9418	0.9334	0.3662	0.3510	0.0073	0.0201	0.1877	0.3904
NV	1.1520	1.1174	0.4337	0.4092	0.0125	0.0207	0.7875	0.2853
NJ	1.2307	1.1816	0.4678	0.4354	0.0087	0.0131	0.8115	0.2965
NM	0.9441	0.9097	0.3589	0.3447	0.0106	0.0124	0.4751	0.3091
NY	1.1734	1.1741	0.4488	0.4356	0.0090	0.0145	0.6095	0.3199
NC	0.9769	0.9443	0.3719	0.3489	0.0094	0.0146	0.6064	0.3300
OH	1.0040	0.9940	0.3833	0.3629	0.0110	0.0218	0.4863	0.3403
OK	0.9203	0.8788	0.3549	0.3298	0.0106	0.0184	0.2625	0.3790
OR	1.0544	1.0491	0.3986	0.3869	0.0128	0.0222	0.5891	0.3020
PA	1.0409	1.0664	0.3985	0.3914	0.0098	0.0197	0.4744	0.3337
RI	1.1346	1.1202	0.4318	0.4160	0.0096	0.0139	0.6121	0.2953
SC	0.9640	0.9169	0.3670	0.3383	0.0101	0.0163	0.5903	0.3392
TN	0.9472	0.9544	0.3608	0.3540	0.0113	0.0166	0.4912	0.3427
TX	0.9842	0.9684	0.3782	0.3639	0.0105	0.0163	0.3466	0.3519
VA	1.0726	1.0164	0.4139	0.3837	0.0074	0.0136	0.3784	0.3204
WA	1.1408	1.0813	0.4357	0.4055	0.0112	0.0151	0.4692	0.3114
WV	0.9265	0.8752	0.3525	0.3262	0.0107	0.0138	0.4575	0.3206
WI	1.0232	1.0429	0.3939	0.3802	0.0079	0.0222	0.3818	0.3345

NOTES: The empirical friendship-gap intercept and slope are replaced by the IV targets. Other empirical targets and assigned parameters are unchanged. Each row is one of the 42 calibrated markets, including DC. y_w, y_b are productivity levels; b_w, b_b are assigned unemployment incomes; δ_w, δ_b are monthly separation probabilities, in fractions; c is the monthly cost per vacancy; χ is the referral effectiveness.

Table C.2: COMMON PARAMETERS AND FIT: IV TARGETS

Parameter	Estimate	Target moment	Empirical	Model
$\bar{\eta}_{ww}$	0.2495	Mean white degree	5.1700	5.2610
$\bar{\eta}_{bb}$	0.1432	Mean black degree	3.7800	3.6864
$\bar{\eta}_x$	2.2462	Friend gap on D: intercept	-0.3541	-0.4479
ζ	8.9557	Friend gap on D: slope	4.4746	4.4356

NOTES: The empirical regression targets are the IV intercept and slope, -0.3541 and 4.4746; friendship means remain the CPS targets. The last two columns compare these targets with model means and fitted friendship-gap coefficients across calibrated states. Degree denotes the number of friends. The four parameters are common across states and estimated jointly. $\bar{\eta}_{ww}, \bar{\eta}_{bb}$ govern same-race formation, while $\bar{\eta}_x, \zeta$ govern cross-race meeting efficiency.

Table C.3: AGGREGATE OUTCOMES: IV TARGETS

	White			Black		
Outcome	Baseline	Counterfactual	Δ	Baseline	Counterfactual	Δ
Average number of friends	5.261	5.683	0.422	3.686	6.124	2.437
of which white friends	5.160	4.917	-0.243	0.549	4.172	3.623
of which black friends	0.101	0.765	0.665	3.137	1.952	-1.186
Average unemployment rate (%)	6.358	6.379	0.021	11.84	9.852	-1.992
Average unemployment duration (weeks)	27.98	28.08	0.100	34.26	27.96	-6.298
Average wage	1.004	1.004	-0.015%	0.948	0.960	1.222%
Welfare (gross)	321.9	321.8	-0.028%	293.6	300.9	2.480%
Welfare (net of networking costs)	316.3	316.1	-0.064%	286.5	293.2	2.360%

NOTES: Baseline and counterfactual refer to the recalibration using the IV friendship-gap targets. The counterfactual sets $D_s = D_{\min}$, the lowest observed dissimilarity in the calibrated sample, holding all other primitives at the values from that recalibration. Averages are taken using race-by-state-population weights. Unemployment is in percent, duration in weeks, and wages use the baseline national residual mean wage of White workers as the common unit. Δ reports changes in counts and weeks, percentage-point changes in unemployment, and percentage changes in wages and welfare. Both gross discounted income and welfare net of networking costs are reported. Appendix C.1 defines aggregation and welfare.

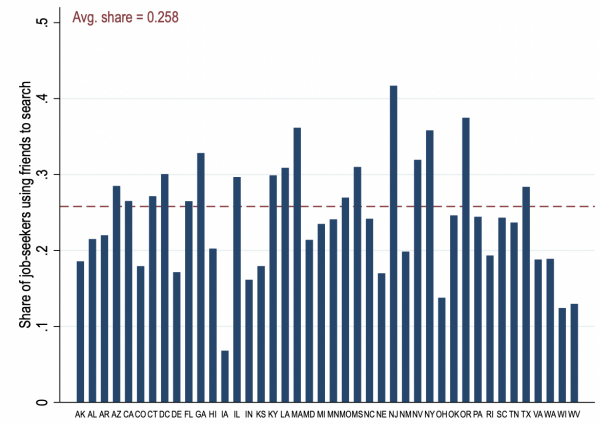
C.3 State-Specific Referral Shares of Hires

We examine how the results change when referrals effectiveness are estimated using race- and state-specific targets (Figure C.1), and race-specific labor market visibility is introduced to match unemployment duration separately by race and state (Figure C.2). Tables C.4 and C.5 report the parameter estimates and fit. The model continues to match the benchmark friendship targets, with lower referral effectiveness and higher estimates of the three meeting-efficiency parameters than in the benchmark.

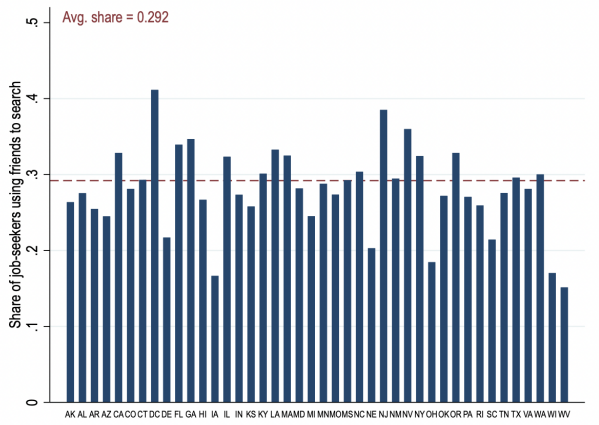
Table C.6 reports the counterfactual. Black workers' unemployment rate falls by about 1.3 percentage point, duration by 4.2 weeks, and wages rise by 0.8 percent. The corresponding benchmark changes are 1.8 percentage points, 5.7 weeks, and 1.1 percent. These smaller labor market responses occur even though Black workers gain slightly more friends than in the benchmark (2.76 vs 2.10). When referrals account for fewer hires in the baseline, an expansion in friendships might not generate as much employment gain.

Figure C.1: SHARE OF UNEMPLOYED JOB SEEKERS USING FRIENDS TO SEARCH FOR JOBS, BY STATE AND RACE

(A) Black workers



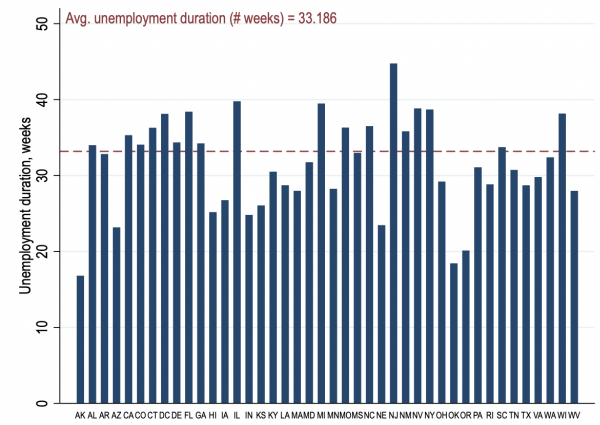
(B) White workers



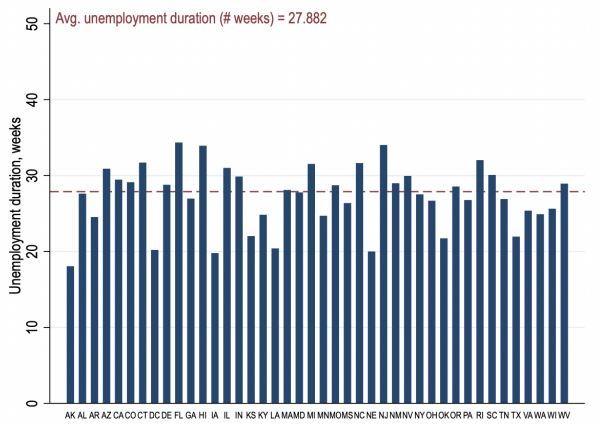
SOURCE: Authors' calculations using the 2008–2018 CPS.
NOTES: Bars report the share of unemployment individual aged 25-55 who report using friends and relative to look for jobs.

Figure C.2: UNEMPLOYMENT DURATION, BY STATE AND RACE

(A) Black workers



(B) White workers



SOURCE: Authors' calculations using the 2008–2018 CPS.
NOTES: Bars report the survey-weighted mean elapsed duration of ongoing unemployment spells, in weeks, among unemployed respondents aged 25-55 in each calibrated market. Panel A reports Black workers and Panel B White workers. The dashed line shows the pooled sample mean for each race.

Table C.4: STATE-LEVEL PARAMETERS: RACE-SPECIFIC VISIBILITY

State	y_w	y_b	b_w	b_b	δ_w	δ_b	c	χ_w	χ_b	ψ_b
AL	0.9513	0.9257	0.3630	0.3421	0.0103	0.0166	0.3415	0.1340	0.1466	0.8797
AK	1.1855	1.1135	0.4564	0.4176	0.0131	0.0282	0.2066	0.1526	0.0884	1.1885
AZ	1.0243	0.9986	0.3893	0.3737	0.0100	0.0205	0.3638	0.1126	0.1619	1.2628
AR	0.9341	0.9105	0.3578	0.3369	0.0106	0.0170	0.2567	0.1336	0.1512	0.7825
CA	1.1780	1.1654	0.4445	0.4269	0.0129	0.0185	0.5409	0.1462	0.1568	0.9129
CO	1.0398	0.9920	0.3986	0.3709	0.0083	0.0132	0.2979	0.1324	0.0974	0.9756
CT	1.2230	1.1829	0.4652	0.4349	0.0095	0.0169	0.4925	0.1253	0.1774	0.9005
DE	1.0926	1.0704	0.4171	0.4023	0.0096	0.0117	0.3366	0.1023	0.1179	0.8864
DC	1.2225	1.2285	0.4767	0.4440	0.0064	0.0209	0.4046	0.2360	0.2248	0.6300
FL	0.9825	0.9775	0.3710	0.3599	0.0104	0.0154	0.5282	0.1502	0.1695	0.9952
GA	1.0029	0.9723	0.3829	0.3605	0.0104	0.0156	0.3952	0.1618	0.1909	0.8099
HI	1.1113	1.0120	0.4259	0.3872	0.0067	0.0106	0.3373	0.1149	0.0936	1.4657
IL	1.0971	1.1026	0.4179	0.3976	0.0093	0.0205	0.4751	0.1442	0.2031	0.8100
IN	0.9939	0.9957	0.3790	0.3650	0.0095	0.0273	0.3519	0.1284	0.1102	1.3886
IA	0.9840	0.9666	0.3816	0.3624	0.0087	0.0167	0.1252	0.1103	0.0675	0.8268
KS	0.9478	0.9493	0.3661	0.3532	0.0090	0.0201	0.1772	0.1462	0.0988	0.9351
KY	0.9530	0.9563	0.3626	0.3529	0.0128	0.0194	0.3108	0.1527	0.1979	0.8165
LA	0.9851	0.9062	0.3788	0.3375	0.0118	0.0176	0.2549	0.1857	0.2427	0.7360
MD	1.1695	1.1664	0.4500	0.4391	0.0077	0.0123	0.3453	0.1314	0.1434	0.9577
MA	1.1873	1.1548	0.4536	0.4310	0.0097	0.0173	0.3947	0.1473	0.2402	0.9492
MI	1.0254	1.0323	0.3875	0.3691	0.0114	0.0232	0.4643	0.1120	0.1715	0.8092
MN	1.0810	1.0724	0.4175	0.3958	0.0078	0.0211	0.2311	0.1478	0.1570	0.9319
MS	0.9319	0.8705	0.3558	0.3212	0.0107	0.0178	0.3439	0.1432	0.2092	0.7800
MO	0.9669	0.9921	0.3702	0.3651	0.0088	0.0166	0.3087	0.1325	0.1766	0.7952
NE	0.9417	0.9340	0.3662	0.3510	0.0075	0.0185	0.1150	0.1324	0.1162	0.8880
NV	1.1514	1.1195	0.4337	0.4092	0.0132	0.0172	0.5833	0.1600	0.1387	0.8202
NJ	1.2305	1.1821	0.4678	0.4354	0.0088	0.0127	0.6147	0.1616	0.2774	0.7209
NM	0.9440	0.9121	0.3589	0.3447	0.0108	0.0096	0.3329	0.1403	0.0848	0.9195
NY	1.1728	1.1750	0.4488	0.4356	0.0094	0.0135	0.4019	0.1492	0.2465	0.6758
NC	0.9770	0.9439	0.3719	0.3489	0.0093	0.0152	0.4117	0.1375	0.1470	0.9438
OH	1.0043	0.9932	0.3833	0.3629	0.0107	0.0239	0.2929	0.0957	0.1074	0.9655
OK	0.9207	0.8772	0.3549	0.3298	0.0100	0.0242	0.1860	0.1544	0.1832	1.2201
OR	1.0544	1.0469	0.3986	0.3869	0.0128	0.0302	0.4411	0.1524	0.1632	1.3216
PA	1.0410	1.0659	0.3985	0.3914	0.0097	0.0207	0.3149	0.1321	0.1732	0.8927
RI	1.1350	1.1176	0.4318	0.4160	0.0093	0.0177	0.4185	0.1135	0.1087	1.2094
SC	0.9642	0.9165	0.3670	0.3383	0.0099	0.0171	0.3558	0.1017	0.1541	0.8586
TN	0.9472	0.9540	0.3608	0.3540	0.0112	0.0174	0.3254	0.1358	0.1597	0.9225
TX	0.9839	0.9691	0.3782	0.3639	0.0109	0.0149	0.2298	0.1594	0.1852	0.7786
VA	1.0722	1.0170	0.4139	0.3837	0.0077	0.0127	0.2487	0.1379	0.0995	0.9615
WA	1.1406	1.0825	0.4357	0.4055	0.0114	0.0135	0.3270	0.1450	0.1078	0.8909
WV	0.9266	0.8734	0.3525	0.3262	0.0106	0.0171	0.2700	0.0806	0.0977	1.0604
WI	1.0227	1.0446	0.3939	0.3802	0.0083	0.0187	0.2138	0.0939	0.0942	0.7090

NOTES: Labor market visibility is race- and state-specific. Other empirical targets and assigned parameters remain at their benchmark values. Each row is one of the 42 calibrated markets, including DC. y_w,y_b are productivity levels; b_w,b_b are assigned unemployment incomes; δ_w,δ_b are monthly separation probabilities, in fractions; c is the monthly cost per vacancy; χ_w,χ_b are referral effectiveness; ψ_b is the labor market visibility for Black workers. ψ_w is normalized to 1.

Table C.5: COMMON PARAMETERS AND FIT: RACE-SPECIFIC VISIBILITY

Parameter	Estimate	Target moment	Empirical	Model
$\bar{\eta}_{ww}$	0.3425	Mean white degree	5.1700	5.2333
$\bar{\eta}_{bb}$	0.1766	Mean black degree	3.7800	3.7159
$\bar{\eta}_{x}$	1.9533	Friend gap on D: intercept	-0.0782	-0.1449
ζ	6.7012	Friend gap on D: slope	3.7355	3.7084

NOTES: Labor market visibility is race- and state-specific; the four friendship targets remain those of the benchmark CPS calibration. The last two columns compare targets with model mean friendship counts and fitted White-Black friendship-gap coefficients. Degree denotes the number of friends. The four parameters are common across states and estimated jointly. $\bar{\eta}_{ww}, \bar{\eta}_{bb}$ govern same-race formation, while $\bar{\eta}_{x}, \zeta$ govern cross-race meeting efficiency.

Table C.6: AGGREGATE OUTCOMES: RACE-SPECIFIC VISIBILITY

	White			Black		
Outcome	Baseline	Counterfactual	Δ	Baseline	Counterfactual	Δ
Average number of friends	5.233	5.693	0.459	3.716	6.477	2.761
of which white friends	5.064	4.824	-0.239	0.924	4.733	3.808
of which black friends	0.170	0.868	0.699	2.792	1.744	-1.048
Average unemployment rate (%)	6.358	6.382	0.025	11.84	10.52	-1.321
Average unemployment duration (weeks)	27.86	27.98	0.117	33.98	29.77	-4.204
Average wage	1.004	1.004	-0.017%	0.948	0.956	0.812%
Welfare (gross)	321.9	321.8	-0.032%	293.6	298.5	1.649%
Welfare (net of networking costs)	319.0	318.8	-0.055%	289.3	293.6	1.468%

NOTES: Baseline and counterfactual refer to the model with state- and race-specific labor market visibility. The counterfactual sets $D_s = D_{\min}$, the lowest observed dissimilarity in the calibrated sample, holding all other primitives at the values from that recalibration. Averages are taken using race-by-state-population weights. Unemployment is in percent, duration in weeks, and wages use the baseline national residual mean wage of White workers as the common unit. Δ reports changes in counts and weeks, percentage-point changes in unemployment, and percentage changes in wages and welfare. Both gross discounted income and welfare net of networking costs are reported. Appendix C.1 defines aggregation and welfare.