# 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 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. 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.

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 and that the relationship persists when we instrument segregation with 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.

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 state-level unemployment rates, unemployment duration, and residual hourly wages in each state, along with aggregate friend 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 the friendship gap and segregation across states to estimate cross-race barriers via indirect inference.

We then reduce cross-race formation barriers in each state to those of the least segregated state in the sample, Alaska, holding all other parameters fixed. On average, Black unemployment duration declines by 5.7 weeks and the 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. Because cross-race links connect one worker from each group, 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 leads 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 inequal-

ity 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 endogenize friendship formation, and allow both the number and racial composition of friends to respond to labor market returns.

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 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 amplifies inequality (Fogli et al., 2026), and place-based policies affect children's skills

[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).

and welfare (Chyn and Daruich, 2025). We instead isolate a labor market channel: barriers to cross-race friendship formation associated with segregation alter access to vacancy information.

# 2 Empirical Facts

## 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 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 (ages 25 and 33) and V (ages 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 unem-

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

[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, none of these other surveys is restricted to the 42 states.

ployment 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

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).

**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. After controlling for demographic characteristics, 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).

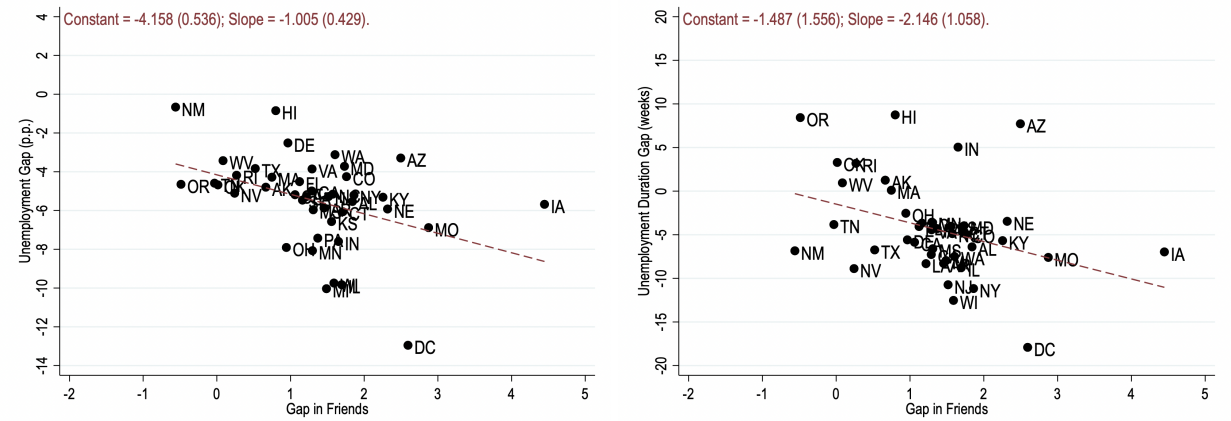
**State-level racial gaps.** Figure 1 shows that US states with larger White-Black friendship gaps also have larger racial unemployment gaps. There is a wide variation in friendship gaps across states; in states such as Oregon and New Mexico, there are basically no gaps, while gaps are larger than two 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))

## 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 across

**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).

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

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

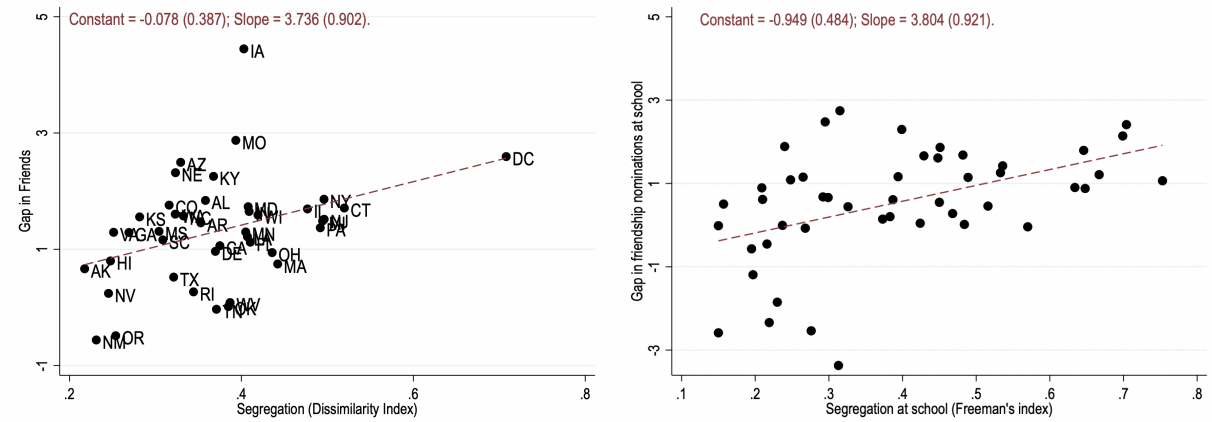
where $\Delta F_s$ is the White-Black difference in mean friendship counts in state $s$. The vector $X_s$ includes state population, the college-educated share, the Black share of the Black-White labor force, and average hourly wages; $\varepsilon_s$ is an error term.

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] In Appendix A.2.5 we discuss possible endogeneity concerns and address them with an

[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.

**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).

instrumental-variables strategy, adapting the approach of Cutler and Glaeser (1997).

**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 (Appendix A.1.4). The relation is statistically significant at 1 percent: a 0.1 increase in this index is associated with a 0.38-nomination larger gap.

# 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 af-

fect both the likelihood that friends can provide referrals and the returns to forming new friendships. The model 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; each link represents one friend to each worker at either end. 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).

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 $\delta_r$, existing friendships dissolve with probability $\lambda$, 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, do not depend on a worker's employment status or realized network, and are symmetric within each group: all group-$r$ workers choose the same effort pair $(e_{rb}, e_{rw})$. We determine these choices in Section 3.5, after deriving their labor market returns.

**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 $\rho_{rg}$ as given. This ratio measures effort from the other group relative to total cross-race effort.[7] 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 where all workers within a group exert the same cross-race effort, selection for new cross-race friendships is uniform within the group and does not favor workers who already have more friends.

**Dissolution and stationary networks.** Existing links dissolve independently with probability $\lambda$. 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

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

[7] 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 $\rho_{bw} = \rho_{wb} = 0$.

Therefore, 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 model information transmission following Calvó-Armengol and Zenou (2005): employed workers pass unused vacancy leads to one of their unemployed friends. Therefore, a worker's access to referrals depends on both the number and the racial composition of her friends, since employment rates can differ across groups and unemployed friends do not pass along vacancies.[8]

**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. An unemployed worker may receive several referrals, but can accept only one job. We use a mean-field approximation to compute job finding rates from group-specific unemployment rates and friendship distributions, so we do not need to track each 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 friends are treated as independent of one another and of direct vacancy leads.[9]

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

[8] 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.

[9] 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.

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 $\Lambda_g$ 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.

**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 $\pi_g$, 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 equilibrium, 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 job filled by a group-$r$ worker. Let $W_r$ and $U_r$ denote the worker's employment and unemployment values before net-

working costs. They satisfy

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

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

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

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

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

An individual takes vacancy supply, group unemployment rates, friends' referral probabilities, and the cross-race effort 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

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

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.[10] The quantitative analysis uses these joint adjustments to assess the labor market consequences of friendship differences.

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

# 4 Quantitative Exercise

**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 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, $\chi_s$, 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 to match hourly residualized wages by race

in each state.[11] 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, $\zeta$, using the OLS estimates of the cross-state relationship between the White-Black friendship gap and residential dissimilarity, as reported in Figure 2A.[12] 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.

## 4.1 The Role of Residential Segregation

To ask how much racial gaps would narrow if every state faced the friendship barriers of Alaska, the least segregated state in our sample, we impose 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.

**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

[11] 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.

[12] 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).

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 faced by White workers shows 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. When more unemployed friends compete for a lead, everyone is less likely to receive it. Hence, congestion can offset the benefit of additional contacts, leading to higher unemployment and longer spells.

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.[13]

**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 level of segregation might respond differently to the counterfactual when the racial composition of their population differ. DC shows 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 friend-

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

**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.

ship 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.

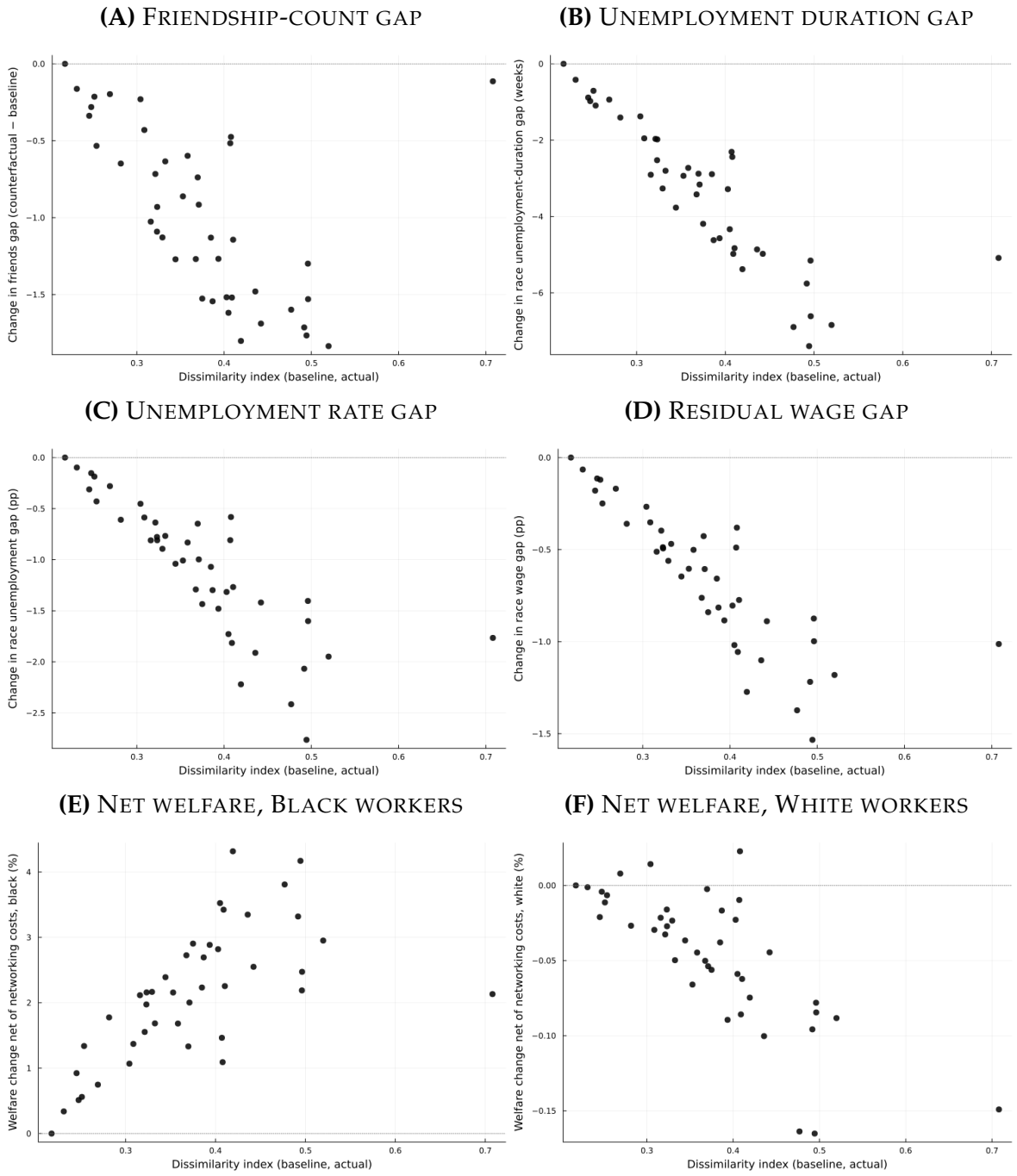
Panel D shows that the residual log wage gap narrows by up to 0.015, implying a 1.5 percent increase in Black wages relative to White wages. The average racial wage gap in the sample is about 5.6 percent. Panels E and F report welfare changes net of networking costs for Black and White workers, respectively. 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 differs 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:

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

**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.

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 $\chi_r$ separately by race and state.

Then, we normalize $\psi_w = 1$ in each state and estimate $\psi_b$ jointly with the cost of posting a 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 unemployment 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, rather than 2.2 percent.

# 5 Conclusion

This paper quantifies the role of friendship formation in racial labor market inequality in the United States. Reducing cross-race friendship barriers to those associated with the least segregated state 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. Our findings highlight friendship formation as a quantitatively important channel linking residential seg-

regation to racial labor market inequality.

# References


**Ananat, Elizabeth Oltmans**, "The Wrong Side(s) of the Tracks: The Causal Effects of Racial Segregation on Urban Poverty and Inequality," *American Economic Journal: Applied Economics*, April 2011, *3* (2), 34–66.

**Bayer, Patrick and Kerwin Kofi Charles**, "Divergent Paths: A New Perspective on Earnings Differences Between Black and White Men Since 1940," *The Quarterly Journal of Economics*, 08 2018, *133* (3), 1459–1501.

**_ , Stephen L. Ross, and Giorgio Topa**, "Place of Work and Place of Residence: Informal Hiring Networks and Labor Market Outcomes," *Journal of Political Economy*, 2008, *116* (6), 1150–1196.

**Bolte, Lukas, Nicole Immorlica, and Matthew O. Jackson**, "The Role of Referrals in Immobility, Inequality, and Inefficiency in Labor Markets," *Journal of Labor Economics*, 2026, *44* (2), 447–479.

**Brouillette, Jean-Félix, Charles I. Jones, and Peter J. Klenow**, "Race and Economic Well-Being in the United States," *American Economic Review: Insights*, December 2025, *7* (4), 429–46.

**Cairó, Isabel and Avi Lipton**, "Labor Market Discrimination and the Racial Unemployment Gap: Can Monetary Policy Make a Difference?," *American Economic Journal: Macroeconomics*, October 2026, *18* (4), 390–428.

**Cajner, Tomaz, Tyler Radler, David Ratner, and Ivan Vidangos**, "Racial Gaps in Labor Market Outcomes in the Last Four Decades and over the Business Cycle," Finance and Economics Discussion Series 2017-071, Board of Governors of the Federal Reserve System, Washington, DC 2017.

**Calvó-Armengol, Antoni and Matthew O. Jackson**, "The Effects of Social Networks on Employment and Inequality," *American Economic Review*, 2004, *94* (3), 426–454.

_ **and** _ , "Networks in Labor Markets: Wage and Employment Dynamics and Inequality," *Journal of Economic Theory*, 2007, *132* (1), 27–46.

_ **and Yves Zenou**, "Job Matching, Social Network and Word-of-Mouth Communication," *Journal of Urban Economics*, 2005, *57* (3), 500–522.

**Charles, Kerwin Kofi and Ming Ching Luoh**, "Male Incarceration, the Marriage Market, and Female Outcomes," *The Review of Economics and Statistics*, 2010, *92* (3), 614–627.

**Chetty, Raj, Matthew O. Jackson, Theresa Kuchler, Johannes Stroebel, Nathaniel Hendren, Robert B. Fluegge, Sara Gong, Federico Gonzalez, Armelle Grondin, Matthew Jacob, Drew Johnston, Martin Koenen, Eduardo Laguna-Muggenburg, Florian Mudekereza, Tom Rutter, Nicolaj Thor, Wilbur Townsend, Ruby Zhang, Mike Bailey, Pablo Barberá, Monica Bhole, and Nils Wernerfelt**, "Social Capital I: Measurement and Associations with Economic Mobility," *Nature*, 2022, *608*, 108–121.

_ **,** _ **,** _ **,** _ **,** _ **,** _ **,** _ **,** _ **,** _ **,** _ **,** _ **,** _ **,** _ **,** _ **,** _ **,** _ **,** _ **,** _ **,** _ **,** _ **,** _ **,** _ **,** _ **, and** _ , "Social Capital II: Determinants of Economic Connectedness," *Nature*, 2022, *608*, 122–134.

_ **, Nathaniel Hendren, Maggie R Jones, and Sonya R Porter**, "Race and Economic Opportunity in the United States: an Intergenerational Perspective," *The Quarterly Journal of Economics*, 05 2020, *135* (2), 711–783.

**Chung, Weonhyeok and Jeonghyeok Kim**, "The Racial Gap in Friendships Among High-Achieving Students," EdWorkingPaper 24-1025, Annenberg Institute at Brown University 2024.

**Chyn, Eric and Diego Daruich**, "An Equilibrium Analysis of the Effects of Neighborhood-Based Interventions on Children," *American Economic Review*, December 2025, *115* (12), 4476–4522.

**Conley, Timothy G, Christian B Hansen, and Peter E Rossi**, "Plausibly exogenous," *Review of Economics and Statistics*, 2012, *94* (1), 260–272.

**Currarini, Sergio, Matthew O. Jackson, and Paolo Pin**, "An Economic Model of Friendship: Homophily, Minorities, and Segregation," *Econometrica*, 2009, *77* (4), 1003–1045.

**_ , _ , and _** , "Identifying the Roles of Race-Based Choice and Chance in High School Friendship Network Formation," *Proceedings of the National Academy of Sciences*, 2010, *107* (11), 4857–4861.

**Cutler, David M and Edward L Glaeser**, "Are ghettos good or bad?," *The Quarterly Journal of Economics*, 1997, *112* (3), 827–872.

**Daly, Mary C., Bart Hobijn, and Joseph H. Pedtke**, "Disappointing Facts about the Black-White Wage Gap," FRBSF Economic Letter 2017-26, Federal Reserve Bank of San Francisco September 2017.

**_ , _ , and _** , "Labor market dynamics and black–white earnings gaps," *Economics Letters*, 2020, *186*, 108807.

**Davern, Michael, Rene Bautista, Jeremy Freese, Pamela Herd, and Stephen L. Morgan**, "General Social Survey 1972–2024," 2025. Machine-readable data file. Principal Investigator, Michael Davern; Co-Principal Investigators, Rene Bautista, Jeremy Freese, Pamela Herd, and Stephen L. Morgan. Sponsored by National Science Foundation. NORC ed. Data accessed from the GSS Data Explorer website.

**Derenoncourt, Ellora, Chi Hyun Kim, Moritz Kuhn, and Moritz Schularick**, "Wealth of Two Nations: The U.S. Racial Wealth Gap, 1860–2020," *The Quarterly Journal of Economics*, 05 2024, *139* (2), 693–750.

**Dustmann, Christian, Albrecht Glitz, Uta Schönberg, and Herbert Brücker**, "Referral-Based Job Search Networks," *Review of Economic Studies*, 2016, *83* (2), 514–546.

**Flood, Sarah, Miriam King, Renae Rodgers, Steven Ruggles, J. Robert Warren, Daniel Backman, Etienne Breton, Grace Cooper, Julia A. Rivera Drew, Stephanie Richards, David Van Riper, and Kari C. W. Williams**, "IPUMS CPS: Version 13.0," 2025.

**Fogli, Alessandra, Veronica Guerrieri, Mark Ponder, and Marta Prato**, "The End of the American Dream? Inequality and Segregation in US Cities," *Journal of Political Economy*, 2026, *134* (4), 1110–1158.

**Freeman, Linton C**, "Segregation in social networks," *Sociological Methods & Research*, 1978, *6* (4), 411–429.

**Galenianos, Manolis**, "Referral Networks and Inequality," *The Economic Journal*, 01 2021, *131* (633), 271–301.

**Hall, Robert E.**, "Employment Fluctuations with Equilibrium Wage Stickiness," *American Economic Review*, March 2005, *95* (1), 50–65.

**Harris, Kathleen Mullan and Robert A. Hummer**, "The National Longitudinal Study of Adolescent to Adult Health (Add Health), Waves I & II, 1994–1996; Wave III, 2001–2002; Wave IV, 2007–2009; Wave V, 2016–2018; Wave VI, 2022–2025 [machine-readable data file and documentation]," 2026.

**Hornstein, Andreas, Per Krusell, and Giovanni L. Violante**, "Frictional Wage Dispersion in Search Models: A Quantitative Assessment," *American Economic Review*, December 2011, *101* (7), 2873–98.

**Ioannides, Yannis M. and Linda Datcher Loury**, "Job Information Networks, Neighborhood Effects, and Inequality," *Journal of Economic Literature*, December 2004, *42* (4), 1056–1093.

**Lleras-Muney, Adriana, Matthew Miller, Shuyang Sheng, and Veronica Sovero**, "Party On: The Labor Market Returns to Social Networks in Adolescence," *Journal of Labor Economics*, 2026, *44* (1), 25–52.

**Logan, Trevon D. and John M. Parman**, "Racial Residential Segregation in the United States," *Journal of Economic Literature*, September 2025, *63* (3), 964–1010.

**Merlino, Luca Paolo, Max Friedrich Steinhardt, and Liam Wren-Lewis**, "More than Just Friends? School Peers and Adult Interracial Relationships," *Journal of Labor Economics*, 2019, *37* (3), 663–713.

_ , _ , **and** _ , "The Long-Run Impact of Childhood Interracial Contact on Residential Segregation," *Journal of Public Economics*, 2024, *239*, 105242.

**Miller, Conrad and Ian M Schmutte**, "The Dynamics of Referral Hiring and Racial Inequality: Evidence from Brazil," Working Paper 29246, National Bureau of Economic Research September 2021.

**Mollenhorst, Gerald, Beate Volker, and Henk Flap**, "Changes in personal relationships: How social contexts affect the emergence and discontinuation of relationships," *Social Networks*, 2014, *37*, 65–80.

**Mouw, Ted**, "Are black workers missing the connection? The effect of spatial distance and employee referrals on interfirm racial segregation," *Demography*, August 2002, *39* (3), 507–528.

_ **and Barbara Entwisle**, "Residential Segregation and Interracial Friendship in Schools," *American Journal of Sociology*, 2006, *112* (2), 394–441.

**National Institute on Minority Health and Health Disparities**, "HDPulse: An Ecosystem of Health Disparities and Specific Populations Health Resources," 2026. Created 7/26/2026.

**Newman, Mark EJ, Steven H Strogatz, and Duncan J Watts**, "Random graphs with arbitrary degree distributions and their applications," *Physical review E*, 2001, *64* (2), 026118.

**Pew Research Center**, "American Trends Panel Wave 131," 2023. Field dates: July 17–23, 2023.

**Pissarides, Christopher A**, "The Unemployment Volatility Puzzle: Is Wage Stickiness The Answer?," *Econometrica*, 2009, *77* (5), 1339–1369.

**Rauh, Christopher and Arnau Valladares-Esteban**, "On the black-white gaps in labor supply and earnings over the lifecycle in the US," *Review of Economic Dynamics*, 2023, *51*, 424–449.

**Ruggles, Steven, Sarah Flood, Matthew Sobek, Daniel Backman, Grace Cooper, Julia A. Rivera Drew, Stephanie Richards, Renae Rodgers, Jonathan Schroeder, and Kari C. W. Williams**, "IPUMS USA: Version 16.0," 2025.

**Sampson, Robert, Jeffrey Morenoff, and Stephen Raudenbush**, "Social Anatomy of Racial and Ethnic Disparities in Violence," *American Journal of Public Health*, 2005, *95*, 224–232.

**Schmutte, Ian M.**, "Job Referral Networks and the Determination of Earnings in Local Labor Markets," *Journal of Labor Economics*, 2015, *33* (1), 1–32.

**Schroeder, Jonathan, David Van Riper, Steven Manson, Grace Cooper, Zachary Krause, Tracy Kugler, Tsu Zhu, and Steven Ruggles**, "IPUMS National Historical Geographic Information System: Version 21.0," 2026.

**Survey Center on American Life**, "2021 American Community Life Survey," 2021. National survey conducted June 11–August 16, 2021.

**Topa, Giorgio**, "Labor Markets and Referrals," in Jess Benhabib, Alberto Bisin, and Matthew O. Jackson, eds., *Handbook of Social Economics*, Vol. 1B, Elsevier, 2011, chapter 22, pp. 1193–1221.

**Treanor, Caitlin**, "Inequality, Referral Networks, and Occupational Segregation," October 2023. Working Paper.

**U.S. Census Bureau**, "1962 Census of Governments—Vol. 1: Government Organization," Census of Governments, U.S. Census Bureau, Washington, DC 1962.

# 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.[14]

**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

[14] 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 using OLS with and without the state-level controls described in Appendix A.2.4. Table A.6 reports OLS estimates in columns (1)-(2). The coefficients on $D_s$ are 3.736 (standard error 0.902) without controls and 3.618 (standard error 1.579) with controls. With controls, a 0.1 increase in dissimilarity is therefore associated with a 0.36-friend larger gap under OLS.

However, the OLS estimates might be biased. Residential segregation may respond to friendship patterns, and 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). Specifically, we instrument $D_s$ with historical government density, $Z_s$, defined in Equation (23).

**Historical fragmentation and identifying assumption.** Our instrument adapts the approach of Cutler and Glaeser (1997). Their argument is that additional municipal jurisdic-

tions 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. Following their strategy, we estimate then following first stage relation:

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

Beyond relevance, identification requires

$$\mathbb{E}[\widetilde{Z}_s \varepsilon_s] = 0, \tag{26}$$

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

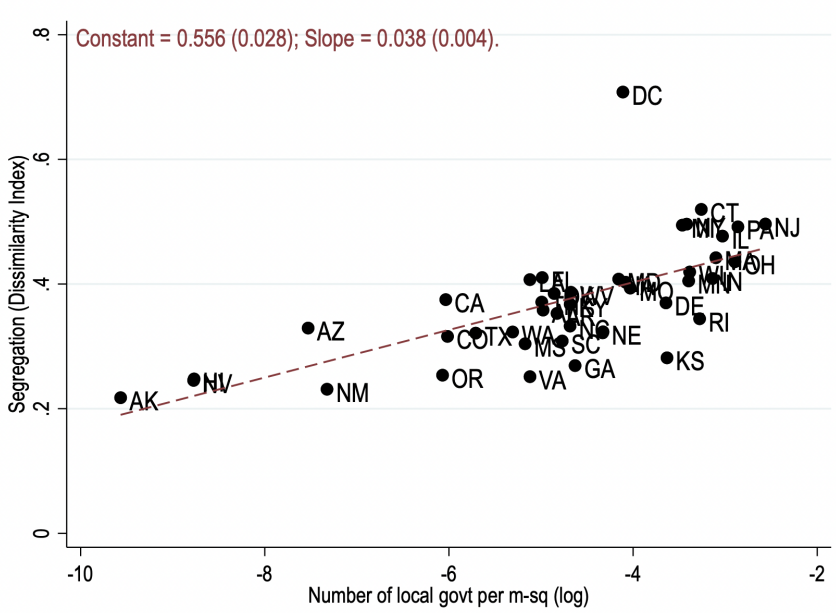
Identification requires historical fragmentation to affect current racial friendship gaps only through measured residential segregation, conditional on state-level controls. The restriction would fail, for example, if persistent jurisdictional boundaries changed school attendance, public services, or opportunities for social contact in ways not captured by $D_s$. We discuss plausible exogeneity of the instrument later in the section.

**Results and magnitudes.** Figure A.1 scatter the first stage relation without controls. Columns (3)-(4) in Table A.6 report first stages estimates. Historical government density predicts higher contemporary segregation: moving to a US state with twice the density of local governments increases the dissimilarity index by 0.038 without controls and 0.034 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.

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,

although the IV estimate with controls is slightly less precise (Table A.6, Columns (5)-(6)).

**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.

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

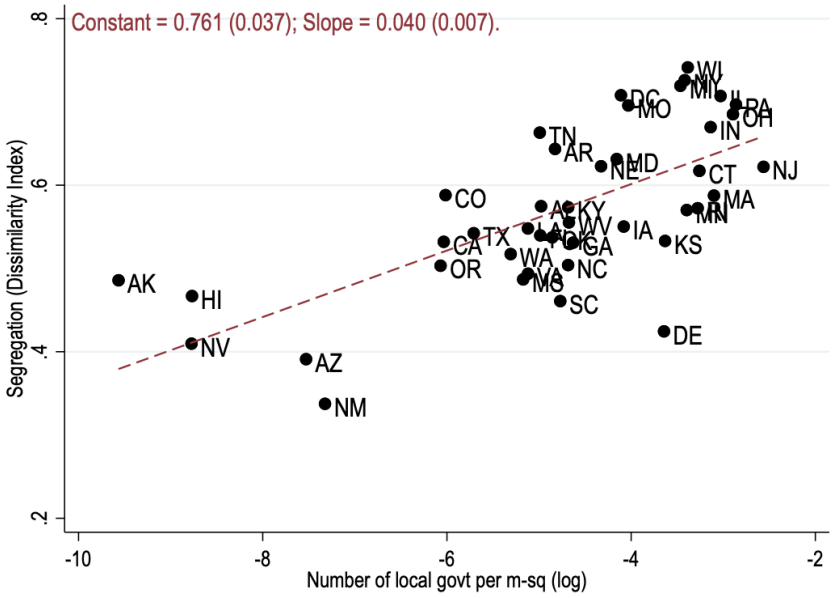
**Plausible exogeneity.** A natural concern with our identification strategy is that the instrument may affect the outcome through channels other than the endogenous regressor, which would violate the exclusion restriction. To assess how much our conclusions depend on this assumption, we follow Conley et al. (2012) and allow the instrument to enter

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

| | | | IV | | | |
|---|---|---|---|---|---|---|
| | OLS | | First stage: $D_s$ | | Second stage: $\Delta N_s$ | |
| | (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 $\Delta N_s$ is the White-Black friendship gap $\Delta F_s$. 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: $\Delta N_s$ | |
| | (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 $\Delta N_s$ is the White-Black friendship gap $\Delta F_s$. 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

the outcome equation directly, with coefficient $\gamma$, that is:

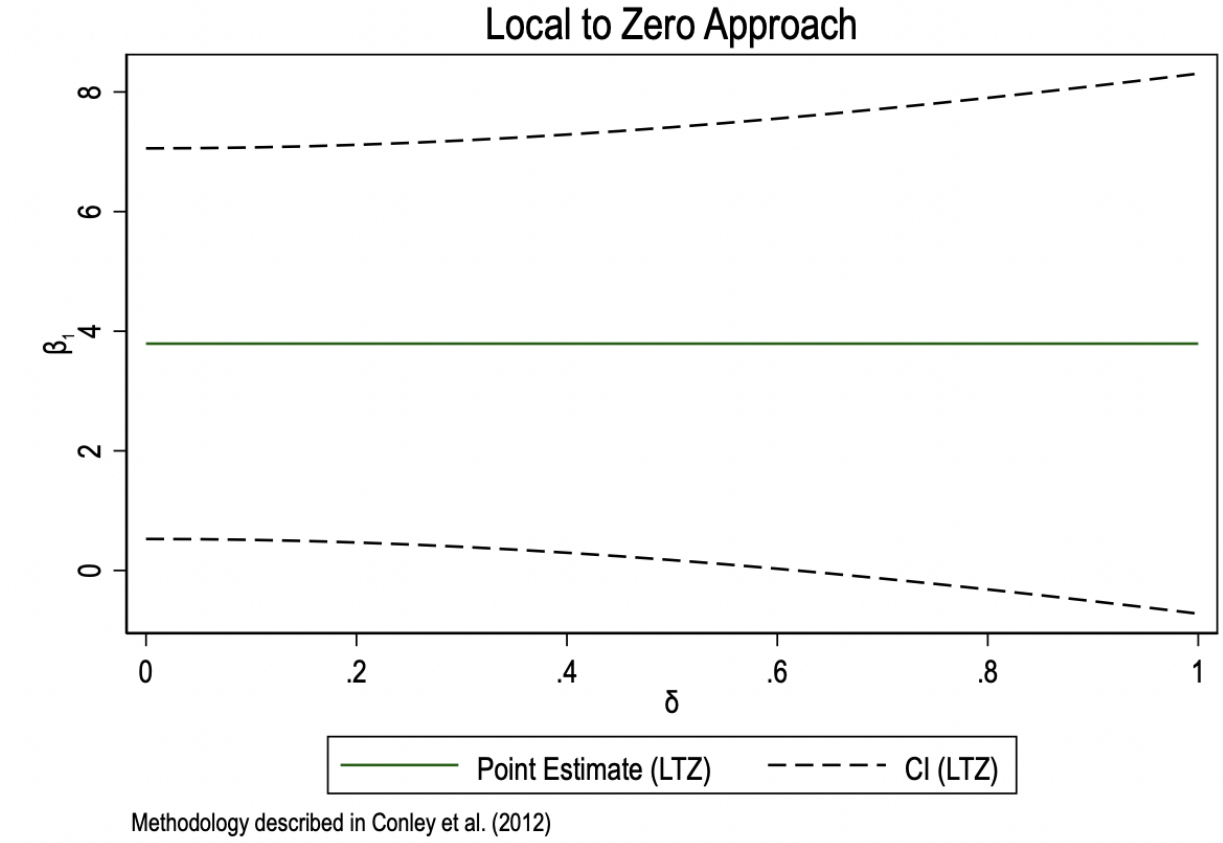
$$\Delta F_s = \beta_0 + \beta_1 D_s + X_s'\gamma + Z_s\eta + \varepsilon_s. \tag{27}$$

We treat $\gamma$ as a random variable with prior $\gamma \sim \mathcal{N}(0, (\delta|\mu|/2)^2)$, where $\mu$ is the reduced-form coefficient of the instrument $Z_s$ on the outcome $\Delta F_s$. The parameter $\delta$ indexes how large a violation we are willing to accept. Setting $\delta = 0$ recovers the IV estimate, while $\delta = 1$ allows the direct effect to be as large as the entire reduced form. Because the prior is centered at zero, we take no stand on the sign of any violation. Hence, departures from exogeneity in either direction widens the confidence interval.

Figure A.3 reports the point estimate and 90 percent confidence interval for $\beta_1$ as $\delta$ ranges from 0 to 1. The point estimate is about 3.8 throughout. The confidence interval widens gradually as $\delta$ increases, and its lower bound stays above zero until $\delta$ reaches about 0.6. Our finding that $\beta_1$ is positive at the 10 percent level therefore survives as long one is willing to rule out, with 95 percent prior probability, direct effects of the instrument larger than about 60 percent of its total reduced-form association with the outcome.

We interpret this as evidence that the sign of our IV estimate is reasonably robust to

**Figure A.3:** PLAUSIBLE EXOGENEITY ANALYSIS OF THE INSTRUMENTAL-VARIABLE ESTIMATE




NOTES: This figure displays instrumental-variable point estimates, $\hat{\beta}_1$, and their 90 percent confidence interval when the direct effect of the instrument $Z_s$ on the outcome $\Delta F_s$ is allowed to range between 0 and 100 percent of their reduced form correlation. Point estimates and confidence intervals are constructed using the methodology proposed by Conley et al. (2012).

plausible departures from the exclusion restriction. To overturn the result, the instrument would need to have a direct effect on the outcome of the same order of magnitude as its entire observed effect, meaning that most of the reduced-form relationship would have to run through channels unrelated to the endogenous regressor. We view this result as supporting the qualitative conclusion that $\beta_1 > 0$.

### 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 $(\mu_b, D)$, 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 $(\nu_b, \nu_w)$, and $(\beta, c, \chi)$, 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.

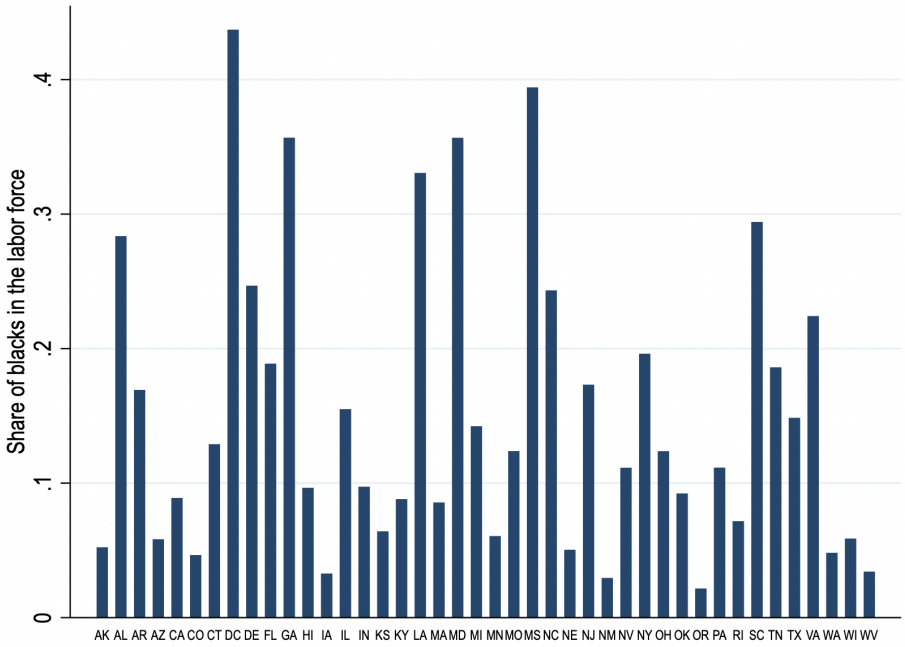
**Unemployment duration.** The target $\widehat{dur}_s$ is the CPS-weighted mean of DURUNEMP, in weeks, among Black and White unemployed respondents in state $s$ over 2008-2018. Figure B.4 reports this target.

**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).

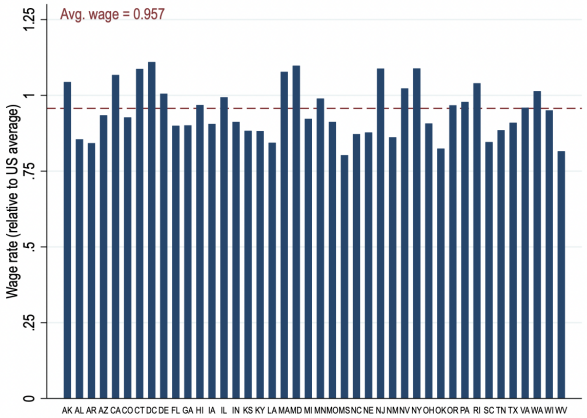
**Figure B.1:** BLACK SHARE OF THE BLACK–WHITE LABOR FORCE, BY STATE



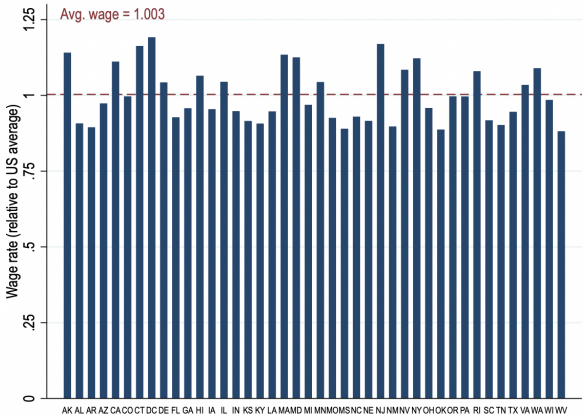

SOURCE: Authors' calculations using the 2008–2018 ACS.
NOTES: Bars report the Black share of the Black–White labor force among respondents aged 25–55.

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

**(A)** Black workers



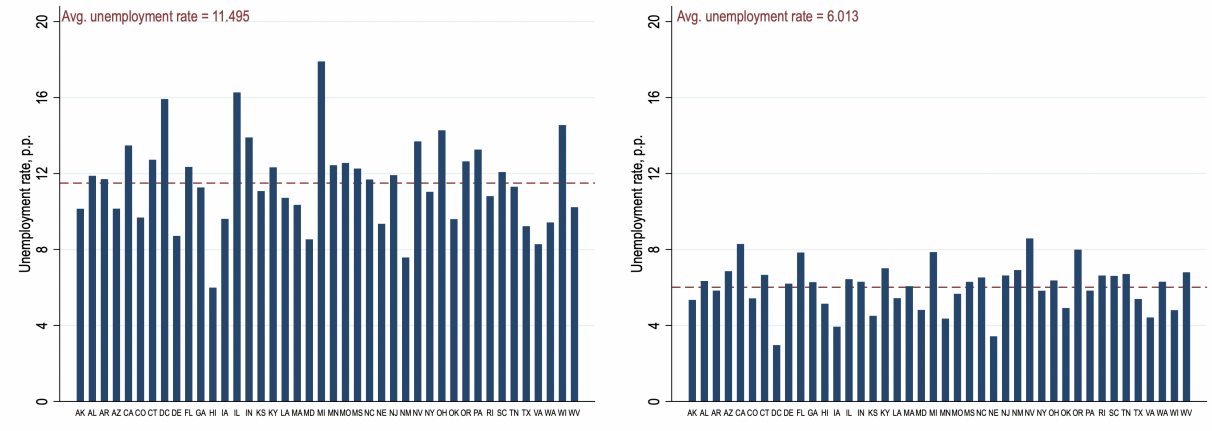

**(B)** White workers




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.

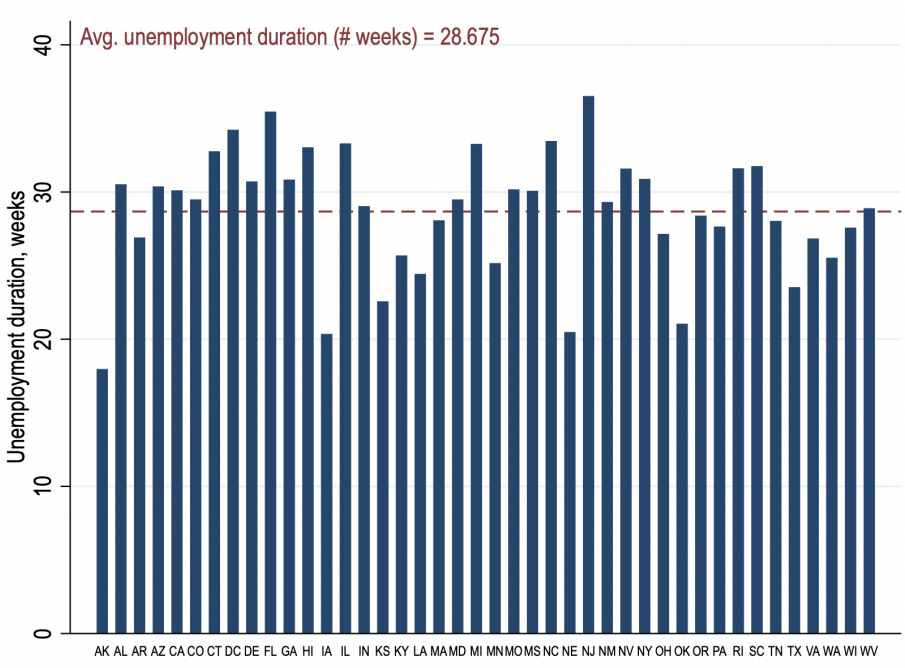
**Figure B.3:** UNEMPLOYMENT RATES, BY STATE AND RACE

**(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* | | |
| $\beta$ | 0.997; 4 percent annual interest | Assigned |
| $\alpha_b, \alpha_w$ | 0.5; equal bargaining weights | Assumed |
| $\kappa$ | 0.40; $b_{r,s} = \kappa \widehat{w}_{r,s}$ | Hall (2005); Hornstein et al. (2011) |
| $\nu_b, \nu_w$ | 1; quadratic effort costs | Assumed |
| $\lambda$ | 0.0087; 48 percent survival over 84 months | Mollenhorst et al. (2014); see text |
| *State-specific parameters* | | |
| $\chi_s$; 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 $\chi_s$ 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 $(v_s, \chi_s)$ 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 $\alpha_r$ 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 $\alpha_r$, 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 $\vartheta$, 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 $\zeta$ 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 $\chi_s$ 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 | $y_w$ | $y_b$ | $b_w$ | $b_b$ | $\delta_w$ | $\delta_b$ | $c$ | $\chi$ |
|---|---|---|---|---|---|---|---|---|
| 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 $\delta_w, \delta_b$ are monthly separation probabilities, reported as fractions. $c$ is the monthly cost per vacancy, and $\chi$ 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 |
| $\zeta$ | 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 $\zeta$ 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.

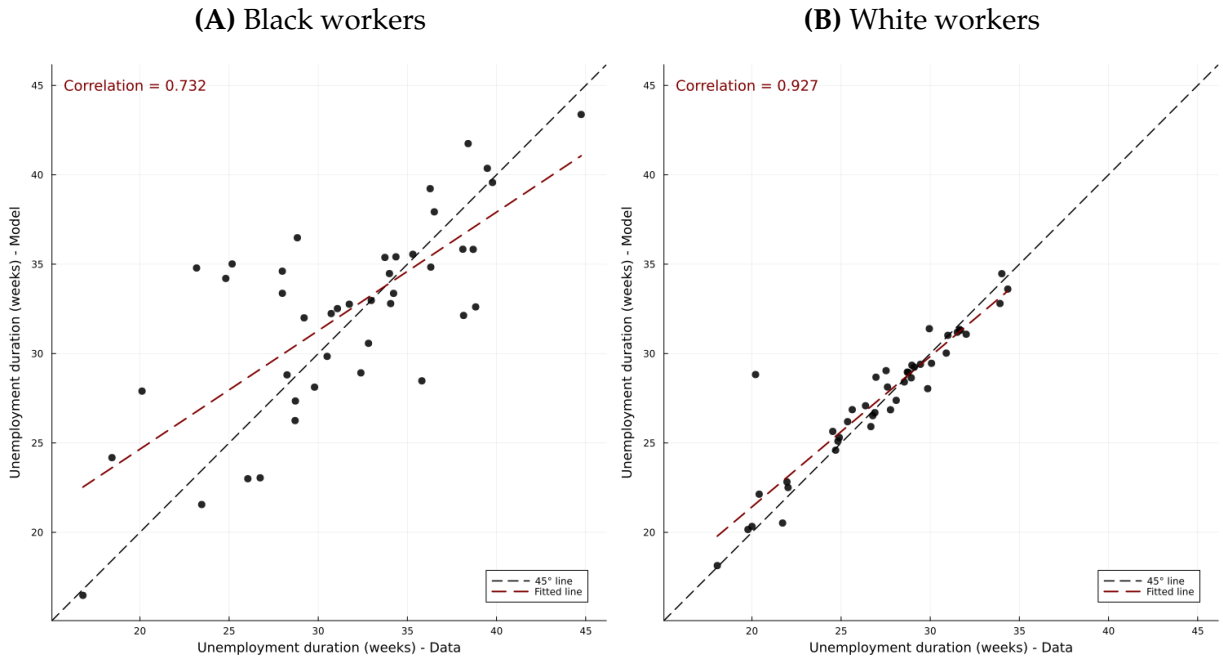
**Friendship-formation parameters.** The estimates are $\bar{\eta}_{ww} = 0.2493$, $\bar{\eta}_{bb} = 0.1444$, $\bar{\eta}_x = 1.8765$, and $\zeta = 8.5023$. At the same effort, the same-race technology produces about 1.73 times as many new friendships for White workers as for Black workers.

The parameter $\bar{\eta}_x$ measures cross-race meeting efficiency at $D = 0$, before accounting for effort from the other group. With the estimated $\zeta$, 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.

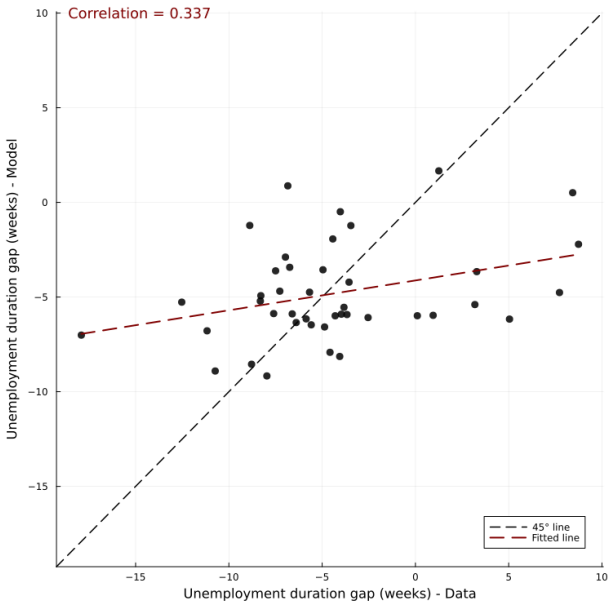
**Untargeted moments.** Figure B.5 compares observed and predicted unemployment duration across states for Black workers (Panel A) and White workers (Panel B). The dashed line is the fitted line. Figure B.6 compares observed and predicted racial unemployment duration gap across states. In both figures, 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 | $y_w$ | $y_b$ | $b_w$ | $b_b$ | $\delta_w$ | $\delta_b$ | $c$ | $\chi$ |
|---|---|---|---|---|---|---|---|---|
| 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; $\delta_w, \delta_b$ are monthly separation probabilities, in fractions; $c$ is the monthly cost per vacancy; $\chi$ 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 |
| $\zeta$ | 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.

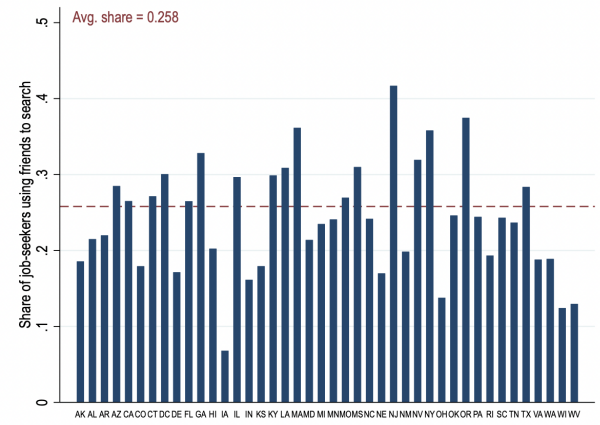
## C.3 State-Specific Referral Shares of Hires

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.

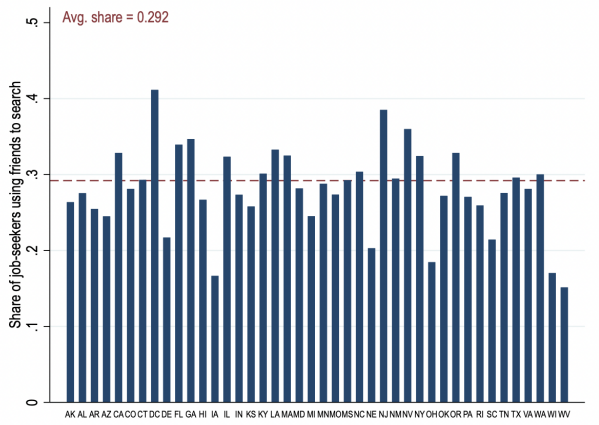
Table C.6 reports the counterfactual. Black workers' unemployment rate falls by about 1.3 percentage point, duration by 4.2 weeks, and wages rise by 0.8 percent. The corresponding benchmark changes are 1.8 percentage points, 5.7 weeks, and 1.1 percent. These smaller labor market responses occur even 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



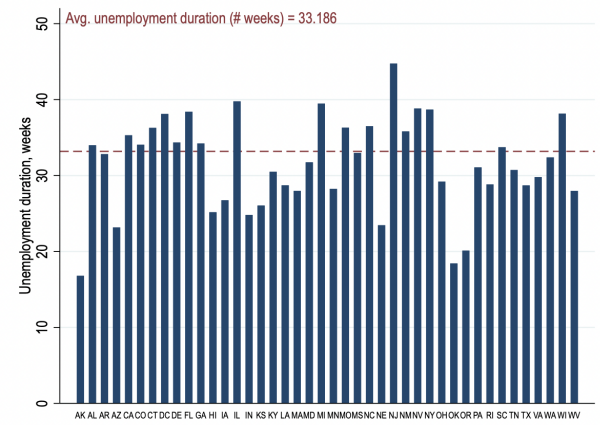

**(B)** White workers



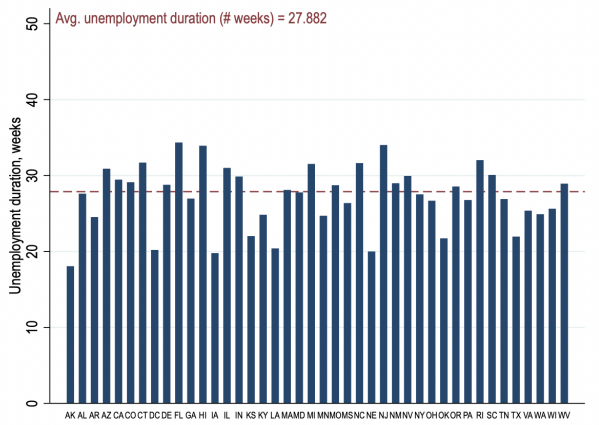

SOURCE: Authors' calculations using the 2008–2018 CPS.
NOTES: Bars report the share of unemployment individual aged 25-55 who report using friends and relative to look for jobs.

**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 | $y_w$ | $y_b$ | $b_w$ | $b_b$ | $\delta_w$ | $\delta_b$ | $c$ | $\chi_w$ | $\chi_b$ | $\psi_b$ |
|---|---|---|---|---|---|---|---|---|---|---|
| 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; $\delta_w$,$\delta_b$ are monthly separation probabilities, in fractions; $c$ is the monthly cost per vacancy; $\chi_w$,$\chi_b$ are referral effectiveness; $\psi_b$ is the labor market visibility for Black workers. $\psi_w$ 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 |
| $\zeta$ | 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.