

THE DYNAMICS OF REFERRAL HIRING AND RACIAL INEQUALITY: EVIDENCE FROM BRAZIL

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Abstract

Social networks play a central role in the job matching process. Networks are also segregated by race. We study how referral hiring affects racial inequality in firm-level labor demand and match quality, and how those relationships evolve over the firm’s life-cycle. We consider a job search model where (a) social networks are racially segregated; (b) firms are more informed about the match quality of job seekers that are referred by an incumbent employee; and (c) a firm’s later hires are less connected than early hires to the founder’s referral network. We test predictions of the model using administrative data from Brazil. Consistent with the model, we find that firms are more likely to hire and less likely to dismiss workers of the same race as the founder, but these differences fade as the firm’s cumulative hires increase. Few firms hire enough employees to reach convergence. Given that founders are disproportionately white, referral hiring can help explain why, relative to white workers, nonwhite workers are more likely to be dismissed from their jobs, have less seniority, and sort to larger employers.

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1 Introduction

Social networks affect which and when job seekers find work, the types of jobs they end up in, and the wages they are paid. They channel information to both employers and workers about the existence of potential matches and the quality of those matches. There are also persistent racial differences in the use and productivity of referrals—differences that arise because social networks tend to form along existing lines of social and economic stratification (McPherson et al., 2001). Recent work suggests that racial disparities in the labor market are driven not only by differences in human capital, but also differences in how workers sort across employers (Gerard et al., forthcoming). While prior work suggests social networks are important, we have little evidence on how much racial disparities are exacerbated due to the widespread use of referrals in hiring.

We study the firm-level implications of referral hiring for racial inequality in labor demand and match quality using detailed employer-employee data from Brazil, a country with well-documented racial disparities in employment rates and wages.¹ We emphasize how the role of referral hiring evolves over a firm’s life-cycle. We present a simple job search model where (a) social networks are racially segregated; (b) firms are more informed about the match quality of job seekers that are referred by an incumbent employee; and (c) a firm’s later hires are less connected than early hires to the founder’s referral network. We confirm four key predictions of the model. First, firms with white (nonwhite) founders are more likely to hire white (nonwhite) employees. Second, these differences disappear as firms’ cumulative number of hires increases. Third, firms are less likely to dismiss recent hires of the same race as the firm’s founder, indicating those hires are less likely to be an ex-post poor match. Fourth, racial differences in dismissal rates are also decreasing in a firm’s cumulative number of hires. Yet few firms hire enough employees to reach convergence in their racial composition of hires or dismissal rates. We then show that our findings, given that founders are disproportionately white, can help explain three stylized facts about racial differences in labor market outcomes: nonwhite workers are more likely to be dismissed by their employers, have less seniority, and sort to larger employers than white workers.

We first describe a simple job search model based on Morgan and Várdy (2009) where a firm posts job vacancies and is matched with job seekers either through referral networks or the external market. At the firm’s entry, referrals are drawn from the founder’s network. Once the firm has additional employees, referrals are drawn from other incumbent employees as well. We assume that referral networks are segregated so that the racial composition of referral candidates tends to reflect the racial composition of incumbent employees. Following much of the literature (Topa, 2019), we also assume that a job seeker’s match-specific productivity is more uncertain when they are matched to the firm via the external market. To match the observation that large employers invest more in formal hiring methods and find a smaller share of their hires via referral (Barron et al., 1987; Holzer, 1987a; Marsden, 1994; Rebien et al., 2020), we further suppose that the firm can

¹See, for example, Silva (1980, 1985); Lovell (1994); Cavalieri and Fernandes (1998); Arcard and d’Hombres (2004); Arias et al. (2004); Matos and Machado (2006); Garia et al. (2009); Reis and Crespo (2015); Gerard et al. (forthcoming).

invest in a (fixed cost) recruitment and screening technology that reduces the relative uncertainty associated with external market candidates.

The model has stark predictions for how a firm’s racial composition of hires and racial differences in dismissal rates evolve over time. The first prediction is that firms with white (nonwhite) founders are more likely to hire white (nonwhite) employees. This follows immediately from the assumption that referral networks are racially segregated. The second prediction is that the racial composition of hires for firms with white and nonwhite founders converges as firms’ cumulative number of hires increases. The correlation between the race of a firm’s founder and its racial composition of recent hires weakens with the firm’s cumulative number of hires for two reasons. First, employees hired via the external market eventually provide referral candidates themselves, pushing the composition of hires towards the composition of external market candidates. Second, firms that expect to hire more employees invest in the hiring technology that reduces the referral share of hires.

The third prediction is that racial differences in dismissal rates are diminishing in a firm’s cumulative number of hires. In the model, referral hires are less likely to be poor matches ex-post, and hence should have lower turnover rates. This turnover advantage should diminish with job tenure as both the employer and worker learn about match quality. The referral share of recent white and nonwhite hires will become more similar as employers’ cumulative hires increase, both because the racial composition of referral and non-referral candidates become more similar and because the overall referral share of hires is smaller at employers that hire more workers. Our proposed mechanism predicts that (a) employers with white (nonwhite) founders and few hires can screen white (nonwhite) job candidates with more precision than nonwhite job candidates on average, and hence there will be racial differences in dismissal rates at employers with few hires and (b) those differences diminish in cumulative hires.

We next provide empirical support for the model. First, we test two assumptions we make in the model: (a) that referral networks are racially segregated and (b) that the use of referral hiring is decreasing in employer size. Both assumptions have empirical support in the existing literature, and we provide additional support in our setting. We do not observe referral networks directly. Instead, we focus on one type of social connection that we can measure in our data: past coworkers. We adopt the empirical strategy of Eliason et al. (2020) to measure the causal effect of social connections on the allocation of workers to jobs. We compare the hiring probability of workers with the same observed characteristics separating from the same plant and who differ only in whether they have a social connection at the destination plant. We show that referral effects on hiring probabilities are substantially larger when the potential hire and incumbent connection are of the same race, consistent with racially segregated referral networks. We also show that the proportional increase in hiring probability associated with having a social connection is decreasing in employer size.

Second, we show that the racial composition of hires for firms with white and nonwhite founders differs substantially at entry, but converges as their cumulative number of hires increases. Early hires at firms with white founders are about 50% more likely to be white than early hires in similar

positions at firms with nonwhite hires. Yet, at firms with a white founder, their nonwhite share of hires increases sharply with cumulative hires. By contrast, the relationship between cumulative and racial composition of hires is relatively flat for firms with a nonwhite founder. The racial composition of hires at firms that have hired 500 or more workers is unrelated to founder race. Yet most firms do not reach this scale—five years after entry, fewer than 1% of remaining firms have made this many hires, accounting for 11% of hires.

Third, we confirm model predictions for turnover patterns. Consistent with firms having superior information about the match quality of referral job candidates, recent hires with pre-existing social connections at their employer are dismissed at substantially lower rates than recent hires without those connections, and this advantage decreases over the job spell. We find that nonwhite employees are dismissed at higher rates than white employees at firms with white founders, while the opposite is true for firms with nonwhite founders. These racial differences in dismissal rates are declining in a firm’s cumulative number of hires and over the course of the job spell.

We then examine the implications of our findings for racial inequality in the labor market. A key market feature for understanding the aggregate implications of referral hiring is that racial disparities in labor market outcomes often coincide with racial differences in entrepreneurship rates. In Brazil, white men and women engage in entrepreneurship at rates about twice as high as nonwhite men and women, where we define entrepreneurship as running a business with at least one paid employee. This suggests that small or young firms will disproportionately favor white job seekers in hiring.

Following this reasoning, we discuss three stylized facts about racial differences in labor market outcomes that are consistent with the dynamics of referral-based hiring: relative to white workers, nonwhite workers (1) are more likely to be dismissed by their employers; (2) have less seniority; and (3) sort to larger employers. All three patterns are driven by employers with white founders. Interestingly, though not subject to much study, the first and third patterns also hold for black and white workers in the United States (Cavounidis et al., 2021; Holzer, 1998; Miller, 2017), suggesting that referral hiring may have similar dynamic implications for racial inequality there.²

We build on a growing economics literature about the role of referral networks in hiring and specifically on sorting and segregation. Like much of the literature, we use variation in the amount of social distance between workers to proxy for the presence of interpersonal connections.³ Our approach to identifying the effects of connections between past co-workers on worker sorting is based on Eliason et al. (2020).⁴ From this literature we adapt tests for whether firms have more information about the match quality of referral candidates (Burks et al., 2015; Brown et al., 2016; Dustmann et al., 2016).⁵

²To the best of our knowledge, seniority or relative tenure within the same employer by race has not been studied in the United States.

³This basic approach was popularized by Bayer et al. (2008) to study the effects on job location of referral interactions among residential neighbors.

⁴Cingano and Rosolia (2012), Hensvik and Skans (2016), and Caldwell and Harmon (2019) take similar approaches to study the effects of co-worker connections on labor market outcomes.

⁵Though not explicitly about referral networks, a related literature documents that hiring managers are more

We contribute to an extensive literature on the role of referral networks in persistent between-group inequality. This literature has generally focused on the United States. Topa (2001) shows that concentration of unemployment across neighborhoods in Chicago can be explained by a model where there are neighborhood interactions in job search, consistent with the model of Calvo-Armengol and Jackson (2004). A subset of this literature focuses on employer behavior, and how employers’ reliance on referrals influences inequality. These papers typically study applications to a single firm (Fernandez et al., 2000; Fernandez and Sosa, 2005; Petersen et al., 2000). We argue that the racial composition of a firm’s referral hires depends critically on the firm’s initial conditions (which we proxy with the race of the founder), but tends to converge to that of the external market over the course of the firm’s life-cycle.⁶

Our paper can be viewed as providing a microfoundation for models of statistical discrimination that assume that decision-makers can screen one group of candidates with more precision than another group (Aigner and Cain, 1977; Lundberg and Startz, 1983; Cornell and Welch, 1996; Morgan and Várdy, 2009). Prior work has justified this assumption by appealing to between-group differences in culture or communication. In our context, small firms with white (nonwhite) founders screen white (nonwhite) job candidates with more precision on average because a higher share of their white (nonwhite) candidates are referrals.

Finally, we contribute to a literature on entrepreneurship and co-racial or co-ethnic hiring. Bates (2006) and Boston (2006) document that, in the United States, black business owners employ workers at higher rates than white business owners, even within the same local labor markets. Both authors argue that increasing black entrepreneurship rates will reduce black unemployment rates. Kerr and Kerr (2021) study co-ethnic hiring by immigrant entrepreneurs in the United States. They find that the average new firm with five or more workers has a co-ethnic share of about 22.5%, with substantial variation by the entrepreneur’s country of origin. Interestingly, they find similar co-ethnic employee shares several years after a firm’s birth. By contrast, we focus on how the composition of *hires* evolves with an employer’s *cumulative hires to date*.

The remainder of the paper is organized as follows. Section 2 sets up our job search model and derives predictions. In Section 3 we describe the Brazilian context and employer-employee data that form the basis of our study in further detail. In Section 4 we test predictions of the model. In Section 5 we address alternative interpretations of our findings. We examine the implications of our findings for racial inequality in Section 6. Section 7 concludes.

likely hire workers of the same race or ethnicity (Giuliano et al., 2009, 2011; Åslund et al., 2014; Benson et al., 2019; Cullen and Perez-Truglia, 2019).

⁶Another subset of this literature focuses on job search behavior. A central question in this literature is whether black job seekers face lower returns to using network-based search methods and, if so, why (Holzer, 1987b; Fernandez and Fernandez-Mateo, 2006; Pedulla and Pager, 2019; DiTomaso, 2013). Our findings also suggest that nonwhite workers are more likely to be socially connected to large firms, which are less dependent on referral hiring.

2 A Job Search Model with Referral Hiring

In this section we describe a simple job search model where a firm’s incumbent employees provide otherwise unobservable information about the productivity of their social connections to the firm. Much of the structure closely follows Morgan and Várdy (2009). We derive predictions for how the racial composition of a firm’s hires varies: (1) with the race of the founder; (2) over time; and (3) with the firm’s size. We also derive predictions for how racial differences in dismissal rates among recent hires vary with these factors.

We consider the sequential hiring decisions of a single firm. The firm must fill n vacancies. The wage for each position is fixed. Consider the firm’s i^{th} vacancy. To fill a vacancy, the firm interviews randomly drawn candidates at a cost $k \geq 0$ per interview. With probability ω , the candidate was referred by a random member of the firm’s existing workforce, and with probability $1 - \omega$, the candidate applied through the external market. Let γ denote the pool a candidate is drawn from, with $\gamma = R$ for referred workers, and $\gamma = E$ for the external market.

Founder or candidate race is denoted by $\rho \in \{W, N\}$. Let $r_i^e \in \{W, N\}$ denote the race of the candidate that fills vacancy i , where the race of the firm’s founder is given by $r_0^e \in \{W, N\}$. Let π_i denote the share of the incumbent workforce with race N (“nonwhite share”) when the firm is filling vacancy i , where

$$\pi_i = \frac{1}{i} \sum_{j=0}^{i-1} \mathbb{1}_{\{r_j^e=N\}}.$$

We assume that incumbent employees only refer workers of the same race. Hence, the probability that a referral candidate for vacancy i is nonwhite is given by π_i . This assumption is stark, but is consistent with well-documented racial homophily in referral networks and social networks more broadly (McPherson et al., 2001; Fernandez and Fernandez-Mateo, 2006; Hellerstein et al., 2011, 2014; Brown et al., 2016). Let $\bar{\pi}$ denote the nonwhite share of external market candidates.

A candidate’s match-specific productivity, θ , equals one if the candidate can perform the job and zero if the candidate cannot. Let $p \equiv \Pr(\theta = 1)$ denote the probability that candidate drawn randomly from the population of job-seekers can perform the job. We assume this probability is independent of the pool a candidate is drawn from (γ) and candidate race (ρ).

At the interview stage, the firm receives a noisy signal S_γ for the candidate’s productivity, $S_\gamma = \theta + \epsilon_\gamma$, where ϵ_γ is normally distributed with mean zero and variance σ_γ^2 . Following the literature, we assume that this signal is more precise for referral matches, so that $\sigma_R^2 < \sigma_E^2$ (Topa, 2019). Later we will allow firms to improve the precision of external market candidates at some cost.

For each vacancy, the timing is as follows. In period 1, the firm draws a random candidate and conducts an interview. On the basis of the candidate’s signal, s , and pool, γ , the firm forms a posterior belief, q , about the candidate’s match-specific productivity. The firm then decides whether to hire the candidate, and period 1 ends.

In period 2 and all subsequent periods, if the firm did not hire in the previous period, the firm

interviews a new candidate the process proceeds as before. If the firm did hire in the previous period, the employee's productivity θ is revealed to the firm. If $\theta = 1$, the employee is retained forever and the firm moves on the filling the next vacancy, if there is one. In that case, the firm receives a payoff with net present value $v > 0$. If $\theta = 0$, then the firm receives a payoff with net present value $-w < 0$ if the firm retains the employee and incurs cost $c > 0$ if the firm dismisses the employee. Throughout, we assume that $c < w$, so that it is always optimal to dismiss unproductive employees. Finally, we assume that the employer is risk-neutral and has a discount factor $\delta \in (0, 1)$.

As Morgan and Várdy (2009) show, the firm's optimal strategy is to impose a uniform success probability threshold, q^* , when deciding whether to hire a candidate. This threshold does not depend on the candidate's pool or race. Define $q_\gamma(s)$ as the firm's posterior belief that a candidate from pool γ with signal s can perform the job; that is, $q_\gamma(s) \equiv \Pr(\theta = 1 | S_\gamma = s)$. By Bayes' rule, this can be written as

$$q_\gamma(s) = \frac{\pi[(s-1)/\sigma_\gamma]p}{\phi[(s-1)/\sigma_\gamma]p + \phi[s/\sigma_\gamma](1-p)},$$

where $\phi(\cdot)$ denote the probability density of a standard Normal random variable.

Let $s_\gamma(q)$ denote the signal realization that corresponds to a given success probability q . Prior to the realization of the signal, but after the firm observes a candidate's pool, the success probability $Q_\gamma = q_\gamma(S_\gamma)$ is a random variable. Now, let $G_\gamma(\cdot)$ denote the cumulative distribution function (CDF) of Q_γ . $G_\gamma(q)$ is given by

$$G_\gamma(q) = p\Phi\left(\frac{s_\gamma(q)-1}{\sigma_\gamma}\right) + (1-p)\Phi\left(\frac{s_\gamma(q)}{\sigma_\gamma}\right),$$

where $\Phi(\cdot)$ denotes the CDF of a Standard Normal random variable.

Similarly, let $G(\cdot)$ denote the CDF of the success probability prior to observing a candidate's pool or signal, where $G(q) = \omega G_R(q) + (1-\omega)G_E(q)$.

2.1 Composition of Hires

We now consider the probability that a hire is nonwhite. Let $r_j^h \in \{W, N\}$ denote the race of hire j for vacancy $v(j)$.

Let α denote the probability that a hire is a referral. α is given by

$$\alpha = \frac{\omega(1 - G_R(q^*))}{\omega(1 - G_R(q^*)) + (1 - \omega)(1 - G_E(q^*))}.$$

Hence, the probability that hire j is nonwhite is given by

$$P(r_j^h = N) = \alpha\pi_{v(j)} + (1 - \alpha)\bar{\pi}.$$

Note that, for an employer where $\pi_{v(j)} < \bar{\pi}$, the nonwhite share of hires is decreasing in the referral share of hires, α .

Similarly, the probability that a *successful* hire for vacancy i is nonwhite is equal to $\alpha'\pi_{v(j)} + (1 -$

$\alpha')\bar{\pi}$, where α' is the probability that a *successful* hire is a referral. In steady state, the nonwhite share of incumbent employees ($\pi_{v(j)}$) is equal to the nonwhite share of the external market ($\bar{\pi}$).

Finally, we allow firms to adjust the precision of the productivity signals they receive in the referral market, so that signal precision $h_E = \frac{1}{\sigma_E^2}$ is a function investment, c_p .⁷ We assume that these costs are fixed relative to a firm's number of vacancies n . Hence, larger firms, or those with more vacancies, invest more in screening precision and have a lower value of h_E . This matches the stylized fact that large employers use more formal recruiting and screening methods and find a smaller share of their hires via referral (Holzer, 1987a; Marsden, 1994; Rebien et al., 2020). Morgan and Várdy (2009) show that, if the firm is sufficiently selective (meaning q^* is sufficiently large), then an increase in a group's signal precision will increase the group's share of hires.

We test four predictions about the composition of hires that derive from this framework. Two predictions follow from our assumptions that the costs of improving signal precision for external market candidates is fixed (and hence large firms hire a smaller share of their workers via referral) and that referral networks are segregated.

1. The share of hires made via referral is declining in employer size.
2. The nonwhite share of referral hires is increasing in the nonwhite share of incumbent employees.

The next two predictions relate to how an employer's racial composition of hires varies over time and with employer size, as given by n . In particular, the composition of an employer's hires moves closer to that of the external market as either cumulative hires or total vacancies increase.

3. The nonwhite share of hires converges to $\bar{\pi}$ as cumulative hires increases.
4. The nonwhite share of hires converges to $\bar{\pi}$ as employer size increases.

For employers with *white* founders, the expected nonwhite share of hires is *increasing* in cumulative hires and employer size.⁸ For employers with *nonwhite* founders, the expected nonwhite share of hires is *decreasing* in cumulative hires and employer size.

2.2 Dismissal Rates

An additional four predictions follow from our assumption that the firm can screen referral candidates with more precision than external market candidates. Morgan and Várdy (2009) show that

⁷Galenianos (2013) and Miller (2017) also allow the firm to control the precision of signals for external market candidates at some cost.

⁸The prediction for employer size is consistent with a literature that examines the effects of formal screening devices on hiring outcomes, including the racial composition of hires. Autor and Scarborough (2008) show that the introduction of job testing at a large retail firm did not reduce minority hiring despite minorities performing significantly worse on the test, and generated productivity gains for both minority and non-minority hires. Holzer et al. (2006) and Wozniak (2015) argue that the use of criminal background checks and drug tests increases black hiring by providing information that is perceived to be more relevant for black candidates.

the group with lower screening precision is dismissed at higher rates. This prediction is standard in the literature (Brown et al., 2016; Topa, 2019). Moreover, this difference in dismissal rates diminishes over the job spell as the firm learns about employee productivity. This prediction is particularly stark in our model, where all employees with $\theta = 1$ are retained forever. However, the same prediction holds in more general models where productivity is continuous or employee productivity is revealed more gradually.

5. Referral hires have lower turnover rates than external market hires.
6. The referral turnover advantage is decreasing in job spell tenure.
7. Within-employer racial differences in dismissal rates are declining in cumulative hires and employer size.
8. Conditional on cumulative hires and employer size, racial differences in dismissal rates are decreasing in job spell tenure.

For employers with *white* founders, expected dismissal rates are higher for nonwhite hires than white hires. That’s because white hires are more likely to be hired via referral. The opposite is true for employers with nonwhite founders.

3 Context and Data

Like the U.S., Brazil’s labor market exhibits significant racial disparities in wages and segregation in employment (Hirata and Soares, 2020; Gerard et al., forthcoming). However, Brazil has few regulations that protect workers against employment discrimination in the private sector on the basis of race (Machado et al., 2019). Therefore, the differences we document in hiring patterns by race are unlikely to be shaped by regulatory pressure, and reflect market or social institutions. We conduct our analysis using administrative linked employer-employee data from Brazil: the *Relação Anual de Informações Sociais* (RAIS), which include a remarkable amount of detail on the characteristics of both workers and their employment contracts.

3.1 Legal and Social Context

Brazil was founded as a race-based slave society and has persistent racial disparities across many socio-economic outcomes. For many decades after the end of slavery, Brazil maintained a national myth that it was a “racial democracy” in which racial disparities were incidental and transitory (Fiola, 1990). Brazil did not construct explicitly racist legal institutions equivalent to the Jim Crow era in the U.S., did not prohibit racial intermarriage, and did not operate under a genetic theory of racial superiority (Daniel, 2010). Perhaps as a result, the government has not adopted systematic affirmative action or equal opportunity policies that apply to the private sector.⁹

⁹In recent years, some state and municipal programs have adopted affirmative action policies, and some universities have begun to impose racial quotas in admissions (Francis and Tannuri-Pianto, 2013).

Given this history, it is not surprising that the sociology of race is also very different in Brazil than the United States. In Brazil, race is associated with skin tone and not so much a categorical trait fixed through inheritance. As a result, there is much more ambiguity and subjectivity in racial classification, which affects how race is measured in survey and administrative data. In official statistics, and in both of our main data sources, there are five main racial categories: *branco* (white), *preto* (black), *pardo* (brown), *amarelo* (yellow), and *indigena* (indigenous). However, the main axis of racial disparity is between the *branco* and the *preto* and *pardo* populations. Therefore, like Cornwell et al. (2017), Hirata and Soares (2020), and Gerard et al. (forthcoming), we follow Telles (2004) in combining *pardo* and *preto* into a single “nonwhite” category, and focus on comparing outcomes for white and nonwhite workers.

Brazil’s labor markets are highly regulated in ways that affect our analysis of hiring. Workers on regular contracts have constitutionally-guaranteed employment protection that kicks in after a 90 day probationary period. If they terminate a worker after the 90 days pass, firms must pay a fine proportional to a workers’ completed tenure. Before that, they can fire workers at will. The presence of these termination costs affects firm’s hiring decisions and the manner by which they evaluate workers during the probationary period. Arnold and Bernstein (2021) show that firing spikes at the 90 day tenure threshold, suggesting that firms do in fact use the 90 day window to continue screening workers before committing to a permanent employment relationship. We take advantage of this labor market feature when testing model predictions for dismissal rates by referral status and race.

Brazil also has a large informal labor market. For us, the key distinction is between formal labor market contracts, which will appear in the administrative data, and informal contracts, which will not. Over the period of our study, the informal sector accounts for between 40 and 60 percent of total employment, with the share declining over time. It is not uncommon for firms to employ some workers on formal contracts and others on informal contracts (Haanwinckel and Soares, 2020).

To provide more context, we summarize data from the Pesquisa Nacional por Amostra de Domicílios (PNAD) between 2002 and 2014. The PNAD is an annual, nationally-representative household survey that collects information on labor market outcomes for both formal and informal workers. We limit to men and women ages 18-65. Statistics by race and gender are reported in Table 1.

[Table 1 about here.]

About 80% of private sector employees report having a valid “carteira de trabalho”, which indicates that they are employed in the formal sector and hence included in the RAIS data. Importantly, rates of formality are similar across racial groups. We define entrepreneurs as those that self-report running a business with at least one paid employee. Overall, 3.3% of men and 1.7% of women are entrepreneurs. Mostly notably, entrepreneurship rates are more than twice as high among whites. For example, 4.4% of white men are entrepreneurs, while 2.2% and 1.9% of mixed race and black men are entrepreneurs.

3.2 RAIS Employer-Employee Data

Our analysis is focused on an extract of the RAIS data over the years 2003–2017. RAIS is a collection of administrative records reported by individual business establishments to the Brazilian labor ministry (*Ministerio do Trabalho* — MTE) for the primary purpose of administering various social security programs.

Each record captures the details of an employment contract between a worker and an establishment during a given year. The recorded details include the worker’s race, education, and gender as reported by the employer. The data also record contract-specific information including average monthly earnings over the year, occupation, the date of hire, and, for jobs that end, the date and cause of separation. We distinguish between employee-initiated separations (“quits”) and employer-initiated separations (“dismissals”). The data include variables that identify both the individual establishment where an employee works, and, separately, the firm or enterprise, that owns the establishment.

[Table 2 about here.]

Table 2 documents significant racial disparities in wages. We limit the sample to worker-firm-year observations for men and women between the ages of 18 and 65 on private sector, indeterminate length contracts for at least 30 hours per week. We report data separately for all worker-firm-year observations, recently hired workers (the first year of a job spell), and recently hired workers at entrant firms.¹⁰ Within each category, we also compare characteristics of white and nonwhite workers. The full data are comprised of 688 million job-year observations, of which 36.5 percent are for nonwhite workers. There is a 20 log point (22 percent) raw wage gap between white and nonwhite workers.¹¹ This may partially be explained by differences in characteristics: white workers are 7.3 percentage points more likely to be college graduates and 0.9 years older on average.

Recently hired workers are more likely to be nonwhite. The raw racial wage gap among new hires is, however, smaller than the overall gap, at 12.5 log points (13 percent). Racial differences between recently hired workers not significantly different when we limit the sample to entrant firms.

We must address a key issue in how race is recorded in RAIS. Cornwell et al. (2017) document that a non-trivial number of workers have different races reported by different employers. This is possible because when a worker changes jobs, their new employer makes an independent record of their demographic characteristics. Cornwell et al. (2017) show that changes in reported race are not independent of residual changes in earnings, and are not explained as simple misreporting. To address this issue, we identify the race for each individual using their modal reported race across all contract-years for which they appear in the data.

¹⁰We describe how we identify entrant firms in more detail in Section 4.3.

¹¹We compute an hourly wage by deflating average monthly earnings by the product of contracted weekly hours and average weeks per month.

3.3 CNPJ Ownership Data

For information on firm ownership we use data from the federal registry of firms, the Cadastro Nacional de Pessoa Juridica (CNPJ), maintained by the Receita Federal do Brazil (RFB).

For a subset of firms, the data report all individual and corporate owners with any stake in the company. For all individuals, the data include either the individual tax identifier (CPF), or a combination of name and a subset of the tax identifier. We use this identifying information to match individuals to the RAIS data. Hence, for all individual owners included in the CNPJ with some formal sector job spell from 2003-2017, we can identify the race of the owner.

4 Testing Model Predictions

In this section we test the model predictions described in Section 2. In Section 4.1 we test whether referral effects on hiring outcomes are declining in employer size and whether referral effects are larger for incumbent employees and connected job seekers of the same race. In Section 4.3 we test whether the racial composition of hires at firms with white and nonwhite founders converge as cumulative hires and employer size increase. In Section 4.4 we test predictions for differences in dismissal rates between referred and non-referred hires. In Section 4.5 we test predictions for dismissal rates by race of hire and employer characteristics.

4.1 Empirical Model of Referral Effects

If referrals are an important hiring channel, we should observe that firms are more likely to hire job seekers with a social connection to one of their incumbent employees. Conversely, workers should be more likely, when obtaining a new job, to move into firms where they have a social connection. Following Eliason et al. (2020), we evaluate the importance of referral-hiring by modeling dyads that pair workers with potential destination firms. In this model, i denotes a worker who is observed to separate from plant j . The binary outcome variable $P_{ijk} = 1$ if i moves from origin plant j to potential destination k . The variable of interest $C_{ijk} = 1$ if i has a social connection to some incumbent employee at destination k and 0 otherwise.

We specify the conditional expectation of P_{ijk} as

$$\log(E(P_{ijk}|X_{ij}, C_{ij})) = \alpha_{jk} + X_{ij}\beta + \lambda C_{ijk}. \quad (1)$$

The parameter λ measures log difference in the probability that firm k hires a worker from origin j when that worker has a social connection to one of k 's incumbent employees relative to the case in which they do not. Identification requires that the existence of a social connection is unrelated to unmeasured factors that influence the probability that i is hired by k . In addition to observable characteristics, X_{ij} , the model allows for unrestricted heterogeneity in hiring by origin-destination pairs through inclusion of α_{jk} . The model therefore measures the contrast in the hiring probability between workers with the same observed characteristics separating from the same plant and who

differ only in the presence of social connection at the destination plant. We estimate the model using the fixed effects Poisson estimator, which yield estimates with a natural proportional interpretation. Specifically, $\exp(\lambda)$ measures the proportional increase in the hiring probability when a coworker link is present, relative to the case where one is not.¹²

Like Eliason et al. (2020), we restrict attention to pairs of plants such that an incumbent worker in firm k has a connection to a worker in j . This restriction is without loss of generality since sample restriction is based on predetermined coworker relationships. In any case, λ is only identified from pairs of firms for which there is variation in the presence of a coworker link and in the outcome.

To measure social connections, C_{ijk} , we use information on whether two workers have worked together in the past. Specifically, a separating worker i is connected to an incumbent worker, e , in k if e and i were both employed working at the same establishment and in the same broad occupation at the same period of time, prior to e 's employment with k .¹³ Following Eliason et al. (2020), we restrict attention to coworking relationships in plants with fewer than 100 employees. This restriction both helps to manage the size of the resulting data and to focus on coworking relationships more likely to involve social interactions.

To assess differences in referral use by employer size, we estimate an extension of (1) that incorporates characteristics of the destination plant:

$$\log(E(P_{ijk}|\cdot)) = \alpha_{jk} + X_{ij}\beta + \left[\lambda + \sum_s \delta_s \mathbb{1}(S_k = s) \right] C_{ijk}. \quad (2)$$

In this extended model, S_k indicates the size class of destination plant k . We report the effect magnitude as $\exp(\hat{\lambda} + \hat{\delta}_s)$, which gives the proportional increase in the probability of hiring for plants in size class s when a coworker link is present relative to the case where it is not.

To assess differences in referral use by race, we estimate an extension that incorporates information on the race of the hired worker and any incumbent worker to whom they are matched

$$\log(E(P_{ijk}|\cdot)) = \alpha_{jk} + X_{ij}\beta + \left[\lambda_{N,N} M_{ijk}^{N,N} + \lambda_{W,N} M_{ijk}^{W,N} + \lambda_{N,W} M_{ijk}^{N,W} + \lambda_{W,W} M_{ijk}^{W,W} \right] C_{ijk}. \quad (3)$$

The indicator $M_{ijk}^{W,N}$ takes a value of one if the hired worker is white and the incumbent worker to whom they are connected in firm k is nonwhite. The coefficient $\lambda^{W,N}$ measures the strength of the referral effect for this type of pairing. The other indicators and coefficients are defined and interpreted similarly.

¹²Note that the fixed effects Poisson estimator only invokes the conditional mean assumption in (1) and a standard strict exogeneity assumption. It is well-suited to binary outcomes and does not require the data follow a Poisson distribution. See Wooldridge (1999). We have also estimated λ under the assumptions of a linear probability model, as in Eliason et al. (2020), and obtain similar results.

¹³We use eight top-level occupation codes from the 2002 vintage of Brazil's occupation classification system, the *Código Brasileiro de Ocupações* (CBO-2002).

4.2 Estimated Referral Effects

We estimate equations (1), (2), and (3) using data covering all of Brazil. To prepare the data, we construct worker-origin-destination dyads for all workers hired between the years 2013–2017. For every dyad, we record a co-worker connection as being present if worker i hired to firm k from firm j was previously a coworker of any incumbent worker in destination k . We require that the coworking spell occurred in a firm other than j or k and ended prior to the year in which i was hired by k . For computational convenience, we perform analysis on a 30 percent random sample of all dyads.

[Table 3 about here.]

Table 3 describes the sample, which is comprised of 118,291,395 dyads. The transitioning worker has a linked coworker connection in 7.2 percent of dyads. We report the size of the potential destination establishment in three groups. The majority of dyads (59.4 percent) involve potential destination firms in the smallest size group (1–99 workers). Of the remaining dyads, 21.7 percent involve potential destinations with 100–499 workers, and 18.9 percent with 500 or more workers. The underlying transitions cover 1,450,133 hired workers (column 1) who are connected to 4,462,676 incumbents (column 2). The shares of hired workers that are white and male are smaller than in the population overall, at 0.319 and 0.576 respectively. These differences reflect the non-randomness in who changes jobs. The demographic characteristics of connected incumbent workers are closer to the population of all workers.

4.2.1 Referral Hiring is Declining in Employer Size

[Figure 1 about here.]

The pattern of results in Figure 1 is consistent our prediction that referral effects are more prominent in smaller establishments. The figure plots referral effects estimated from equation (2) for dyads disaggregated by the size of the hiring establishment. The plotted effects measure the proportional increase in the probability a worker is hired when a linked coworker is present. In establishments with fewer than four workers, the presence of a past coworker is associated with an increased hiring probability by a factor of 2.60 over the baseline. For firms with over 1000 workers, the estimated effect is 1.59 over the baseline. Aside from the very smallest establishments, the decline is perfectly monotonic. To put these effect sizes in context, in their study of Sweden, Eliason et al. (2020) find that having a coworker link present increases the likelihood of a hire by a factor of 10.

[Table 4 about here.]

We compare alternative models of the referral effects in Table 4. For each model, we report the scaled effect size along with the estimated parameter, λ , from the referral model. The estimated

referral effect across the full sample is 1.863, consistent with the evidence in Eliason et al. (2020), which suggests a similarly strong evidence of coworker referrals. For ease of presentation, we report estimates across three coarse size groups: 1–99 employees, 100–499 employees, and 500+ employees. As in Figure 1, the effects are larger — economically and statistically — for small hiring establishments. The referral effect in firms with 1–99 employees is 2.815 over baseline. For establishments with 500+ workers, it is 1.635 over baseline. In short, referral hiring is present in all establishments, but substantially less so in large establishments.

This finding is consistent with larger establishments having more formalized human resources (HR) practices. This relationship is corroborated in the Brazilian wave of the World Management Survey (WMS). The WMS scores firms on their adoption of formal management practices across several domains, including people management, operations, and performance targeting (Bloom et al., 2014). Appendix Figure B.1 shows that the adoption of formal people management and overall management practices are increasing in firm size.¹⁴ The WMS for Brazil only covers a small sample (815 observations) on medium-sized manufacturing firms. However, we can provide complementary evidence that the adoption of formal human resource management patterns is increasing in employer size more generally. For all firms and establishments in RAIS, we proxy for HR formality using the share of an establishment’s employees that are in HR-related occupations.¹⁵ Appendix Figure B.2 plots the HR share of an employer’s workforce by employer size, where employers are defined at either the establishment or firm level. The relationship is increasing for either measure.

4.2.2 Referral Effects by Incumbent and Job Seeker Race

In the final column, we document differences in estimated referral effects according to the match of the race between the hired worker and the incumbent worker at a potential destination firm to which they are linked through a past co-working relationship. The coefficient estimates, which correspond to equation (3), show that referral effects are substantially larger when both workers are of the same race. Referral effects also seem to be slightly stronger for nonwhite pairs. Altogether, these results are consistent with a large literature documenting homophily in social interactions and either indicate that coworker connections are a stronger proxy for actual social interaction when workers are of the same race, or that referral effects are more likely between workers who know one another when they are of the same race.

The empirical model investigates four possible pairings: nonwhite hired worker linked to a nonwhite incumbent; nonwhite hire linked to white incumbent, and so on. The omitted category corresponds to dyads where there is no coworker connection ($C_{ijk} = 0$). Converting the estimates to relative effect sizes, for dyads in which a nonwhite hired worker is linked to a nonwhite incumbent, the coworker referral effect increases the hiring probability by factor of 2.044 relative to the case

¹⁴Cornwell et al. (forthcoming) show that the positive relationship between employer size and the WMS people management score continues to hold when conditioning on other observable characteristics.

¹⁵This includes the following occupations: *administrador* (administrator); *diretor de recursos humanos* (human resources director); *gerente de recursos humanos* (human resources manager); and *gerente de departamento pessoal* (personal department manager).

where no coworker link is present. When a nonwhite worker is connected to a white incumbent, the referral effect is just 1.326. The estimated effect is negligible, at 1.072 for dyads where white hires are linked to nonwhite incumbents. Confirming that the race match matters, referral effects are strongest for dyads with white workers linked to white incumbents: the referral effect is 2.323.

4.3 Racial Composition of Hires Converges with Cumulative Hires and Size

We predict that the racial composition of new hires for an employer will be correlated with the race of the founder, but this correlation is decreasing in the employer’s (a) cumulative number of hires and (b) size (n from the model). As the employer’s cumulative number of hires and size increase, new hires are further removed from the founder’s referral network. Together, these predictions imply that, in the cross-section, the nonwhite share of hires is increasing in cumulative hires for firms with white founders and decreasing in cumulative hires for firms with nonwhite founders. We first test for this pattern in the cross-section, and then test whether the pattern holds within firms and between firms with more or fewer total hires, which roughly corresponds to predictions (a) and (b).

We take all firms that we observe as entrants in the RAIS data. For multi-establishment firms, we take the first establishment observed for the firm, if we observe that establishment’s year of entry. We refer to these establishments and single-plant firms as *headquarter (HQ)* establishments. We further restrict to establishments that enter the RAIS data with 1-49 employees as of December 31st in its year of entry. We are left with a sample of about 1.5 million establishments. Appendix Table B.1 provides descriptive statistics for these entrant HQ establishments. We refer to HQ establishments and firms interchangeably for the remainder of the paper.

We characterize founder race in two ways. First, following standard practice in the entrepreneurship literature (Kerr and Kerr, 2017; Azoulay et al., 2020; Babina, 2020; Bernstein et al., 2021), we infer the race of a firm’s founder using the race of the highest paid manager in the HQ establishment at entry.¹⁶ Second, we infer the race of a firm’s founder using the racial composition of ownership. We classify firms where more than 50% of ownership is white as having a white founder and firms where more than 50% of ownership is nonwhite as having a nonwhite founder. We then ask how the composition of new hires in subsequent years evolves with the establishment’s cumulative number of hires. For firms with a white founder, we predict the nonwhite share of hires to be (weakly) increasing in cumulative hires. For firms with a nonwhite founder, we predict the nonwhite share of hires to be (weakly) decreasing in cumulative hires. We predict that the nonwhite share of hires for HQ establishments of firms with white and nonwhite founders will converge as their cumulative hires increase, so that when cumulative hires is sufficiently high, the racial composition of hires is

¹⁶For HQ establishments with no employee with a manager occupation code, we take the highest paid employee. If multiple people have the same exact wage at the top of the distribution, we pick one randomly. Using tax data on S corporations in the United States, Azoulay et al. (2020) find 90 percent of owner-workers are among the top three earners in the firm during the first year. Note that while this procedure may not identify the relevant founder in some cases, the race of the individual identified by this procedure is likely highly correlated with the race of the founder.

not related to the race of the founder.

We estimate regression models of the form

$$\begin{aligned} \log(E(\text{NONWHITE}_{it}|\cdot)) = & \sum_n \sum_r \eta^{n,r} \times \mathbb{1}_{\{N(J,t)=n\}} \times \mathbb{1}_{\{R(J)=r\}} \\ & + \tau_t + \mu_m(J(i,t)) + \omega_{o(i,t)} + \epsilon_{it} \end{aligned} \quad (4)$$

via Poisson quasi maximum likelihood (Correia et al., 2020), where each observation is a new hire, i indexes workers, t indexes time, and $J(i, t)$ indexes the establishment. We limit to hires made after the year of the firm’s entry. NONWHITE_{it} is an indicator for whether the new hire is nonwhite. $R(J)$ categorizes establishments by founder race. $N(J, t)$ indexes an employer’s cumulative hires to date. We group hires into increments of five: hires 1-5, 6-10, 11-15, and so on. The omitted category is the first increment of hires for establishments with white founders. τ_t are year fixed effects, $\mu_m(J(i, t))$ are microregion fixed effects (which we use to approximate local labor markets), and $\omega_{o(i, t)}$ are fixed effects for 2-digit occupation.

We plot the coefficient estimates in Panel A of Figure 2. Here we infer founder race from the race of the top-paid manager. (We plot analogous results where we infer founder race using the racial composition of ownership in Appendix Figure B.3; the results are similar.) The pattern fits our predictions. For early hires, the racial composition of new hires is closely tied to founder race. For the first few hires, in Panel A the probability that the hire is nonwhite is about 40 log points higher at firms with a nonwhite founder compared to firms with a white founder. This gap declines steeply in cumulative hires. By the 50th hire, this gap declines to about 20 log points, and 10 log points by the 200th hire. By the 500th hire, the racial composition of hires at firms with white and nonwhite founders is statistically indistinguishable.

[Figure 2 about here.]

The pattern illustrated in Panel A of Figure 2 may both reflect the within-firm evolution in the racial composition of hires and differences in composition for firms with more or fewer total hires. The model predicts that both channels will contribute to the cross-sectional relationship. We next distinguish between these channels.

We test for whether the nonwhite share of hires varies as predicted both *within* establishments and *between* establishments. We estimate equation (4), but allow the η coefficients to vary with a firm’s total observed hires. Specifically, we estimate

$$\begin{aligned} \log(E(\text{NONWHITE}_{it}|\cdot)) = & \sum_s \sum_n \sum_r \eta^{s,n,r} \times \mathbb{1}_{\{S(J)=s\}} \times \mathbb{1}_{\{N(J,t)=n\}} \times \mathbb{1}_{\{R(J)=r\}} \\ & + \tau_t + \mu_m(J(i,t)) + \omega_{o(i,t)} + \epsilon_{it} \end{aligned} \quad (5)$$

where $S(J)$ categorizes firms by their total observed hires: 50-249, 250-499, and 500+. We restrict estimation to hires 1-50 for firms with 50-249 total observed hires, hires 1-250 for firms with 250-

499 total observed hires, and hires 1-500 for firms with 500+ total observed hires. This restriction maintains a balanced sample of firms contributing to the estimation of $\eta^{s,n,r}$ coefficients.

The results are presented in Panel B of Figure 2. For establishments with white founders, the pattern of coefficients is similar to what we found in Figure 2, though the magnitude of change is smaller. The relationship between an establishment’s nonwhite share of hires and cumulative hires is increasing and concave. By the 200th hire, the probability that the hire is nonwhite is about 20 log points larger than that same probability for the first hire. For establishments with nonwhite founders, the relationship is negative rather than flat, but the magnitude of change is smaller than that for establishments with white founders.

We extend the analysis in two ways in the Appendix. First, we conduct an analogous exercise for new establishments that are subsidiaries of existing firms. We characterize establishments by the racial composition of the firm’s incumbent employees. The findings are similar (see Figure B.5). Early on, establishments from firms with mostly white employees are more likely to hire white workers than peer establishments from firms with mostly nonwhite employees. But these differences disappear as the establishment’s cumulative hires increase.

Second, we examine whether the patterns documented here vary with other firm characteristics. Motivated by Gerard et al. (forthcoming), who find that nonwhite workers are underrepresented at high-paying firms, we estimate equation (4) separately by firm pay premium quintile, where we estimate pay premiums using the canonical two-way fixed effect model of Abowd et al. (1999). We find the same patterns for low-paying and high-paying firms (see Appendix Figure B.6).

4.4 Referral Hiring and Learning About Match Quality

A common explanation for why employers use referral networks in hiring is that they can obtain more information about the match quality of potential referral hires (Topa, 2019). A growing literature tests the empirical implications of this class of referral-based job search models (Brown et al., 2016). These papers test whether, within a firm, referral hires have lower turnover relative to non-referral hires, but these differences dissipate with tenure.

We ask whether referral hires have lower dismissal rates than non-referral hires, and how differences in dismissal rates evolve with tenure. We estimate a discrete-time hazard model and compare hazard rates within the same establishment and occupation for hires that are connected and not connected to an incumbent employee at their time of hiring. We expand our job spells data into a job spell by time period data set, where each observation represents a job spell and 15-day tenure period, where periods are indexed by p .¹⁷

We estimate regression models of the form

$$\log(E(\text{DISMISSED}_{iJ(i,t)p}|\cdot)) = \sum_p \theta^p \text{CONNECTED}_{iJ(i,t)} \mathbb{1}_p + \sigma_p + \tau_t + \omega_{o(i,t)} + \psi_{J(i,t)} + \epsilon_{it} \quad (6)$$

¹⁷We are missing data on the specific date of separation for the years 2011-2013. For this reason, we exclude job spells that begin in 2009-2013 from the analysis.

where $\text{DISMISSED}_{iJ(i,t)p}$ is indicator for whether the establishment $J(i,t)$ dismisses employee i in tenure period p ; $\text{CONNECTED}_{iJ(i,t)t}$ is an indicator for whether hire i has a connection at establishment $J(i,t)$ at the time they are hired; and $\psi_{J(i,t)}$ are establishment fixed effects. The coefficients θ^p convey the differences in log dismissal hazard rates in tenure period p between connected and non-connected hires conditional on year, occupation, and establishment fixed effects.

Panel A of Figure 3 plots dismissal rates by tenure for connected and non-connected hires as implied by equation (6). There are two points to note. First, dismissal rates for non-connected hires exceed dismissal rates for connected hires at all depicted tenure levels. This is particularly salient in the period running up to the end of the 90-day probationary period, where dismissal rates spike.¹⁸ While both non-connected and connected hires experience a sharp increase in dismissal rates, the spike is markedly larger for non-connected hires. Second, the gap in dismissal rates generally dissipates over time following the 90-day spike, with much of the closing in the gap occurring after about 250 days on the job.

[Figure 3 about here.]

To further summarize differences in dismissal rates between connected and non-connected hires, we focus on dismissals during the probationary period. We estimate regression models of the form

$$\log(E(\text{DISMISSED-3M}_{it}|\cdot)) = \theta \text{CONNECTED}_{iJ(i,t)} + \tau_t + \omega_{o(i,t)} + \psi_{J(i,t)} + \epsilon_{it} \quad (7)$$

where DISMISSED-3M_{it} is an indicator for dismissal within 3 months of the hire date.

Appendix Table B.4 presents θ coefficient estimates for several specifications, where the vary the granularity of controls across specifications. These θ coefficient estimates vary from -1.751 to -1.890, indicating that non-connected hires are more six times more likely to be dismissed during the probationary period than their connected peers.

Note that we only capture one type of social connection in our data, previous co-workers, and turnover patterns may vary with the type of connection. Nonetheless, we interpret this striking pattern as evidence the referral hires have lower dismissal rates than comparable non-referral hires.

Overall, our findings are consistent with job search models where referral networks provide information to employers about a job candidate’s match quality. If indeed the hiring dynamics documented in Section 4.3 are driven by referral hiring, racial differences in dismissal rates for recent hires favor hires of the same race as the establishment’s founder, but are decreasing in an establishment’s total number of hires.

¹⁸Arnold and Bernstein (2021) exploit this bunching in dismissals at the end of the probationary period to estimate the equilibrium effects of employment protection legislation.

4.5 Racial Disparities in Dismissal Rates Are Decreasing in Total Hires

We test whether within-firm racial differences in dismissal rates are decreasing in total hires. We return to our sample of entrant firms and estimate regression models of the form

$$\log(E(\text{DISMISSED-3M}_{it}|\cdot)) = \tau_t + \omega_{o(i,t)} + \psi_{J(i,t)} + \psi_{J(i,t)}^{NW} + \epsilon_{it} \quad (8)$$

where $\psi_{J(i,t)}$ are firm fixed effects and $\psi_{J(i,t)}^{NW}$ are firm by nonwhite fixed effects. Hence, $\psi_{J(i,t)}^{NW}$ is the firm-specific racial disparity in log 3-month dismissal rates.

Figure 4 depicts the average of $\psi_{J(i,t)}^{NW}$ as a function of a firm’s total observed hires and race of founder. We limit to firms where we observe at least 20 hires and then take an average of $\psi_{J(i,t)}^{NW}$ across firms, weighting by each firm’s number of observed hires. At firms with 20-49 hires and white founders, the 3-month dismissal rate is about 18% higher for nonwhite hires. This declines to a 5% gap at firms with 500 or more hires. By contrast, at firms with 20-49 hires and nonwhite founders, the 3-month dismissal rate is about 5% *lower* for nonwhite hires. There is essentially no racial difference in dismissal rates at firms with nonwhite founders and 250 or more hires.

[Figure 4 about here.]

If the pattern we document in Figure 4 is driven by the fact that racial differences in the referral share of hires is diminishing with total hires, then the relationship between racial disparities in dismissal rates and total hires should be muted with tenure. We test by re-estimating equation (8) but replacing the outcome with an indicator for dismissal in the first 18 months of the spell. We plot the corresponding coefficients also in Figure 4. Reassuringly, we find that the relationship between total hires and the racial disparity in 18-month dismissal rates is relatively flat.

5 Alternative Interpretations

We interpret the evidence presented in the previous section as consistent with the job search model presented in Section 2. In this section we consider alternative interpretations of the patterns we document.

5.1 Human Capital

One alternative explanation for our findings is that they are driven by differences between white and nonwhite workers in human capital or preferences over occupations. Firms with white and nonwhite founders may hire for positions that tend to be filled by nonwhite and white workers later in the firm’s life-cycle, respectively. Equation (4) includes fixed effects for two-digit occupation; however, the positions that firms fill may vary in unobservable ways over the firm life-cycle.

To assess this explanation, we examine how the occupational composition of hires varies over the firm life-cycle for firms with white and nonwhite founders. For each two-digit occupation, we

measure the nonwhite share of workers hired into that occupation, $\bar{\omega}_o$. We then estimate models analogous to equation (4), replacing the outcome with $\bar{\omega}_o$:

$$\begin{aligned} \log(E(\bar{\omega}_{o(i,t)}|\cdot)) &= \sum_n \sum_r \eta^{n,r} \times \mathbb{1}_{\{N(J,t)=n\}} \times \mathbb{1}_{\{R(J)=r\}} \\ &\quad + \tau_t + \mu_{m(J(i,t))} + \epsilon_{it}. \end{aligned} \tag{9}$$

Appendix Figure B.9 plots the $\eta^{n,r}$ coefficient estimates. The value of $\bar{\omega}_{o(i,t)}$ is increasing slightly over the firm’s life-cycle. However, this is true for both firms with white and nonwhite founders. Racial differences in human capital do not appear to explain our findings.

5.2 Taste-Based Discrimination

A second alternative explanation is that employers exhibit taste-based discrimination. Some establishments with white founders may prefer to employ white workers conditional on match productivity, and are less likely to grow as a result. This could generate an increasing relationship between cumulative hires and the probability that a hire is nonwhite, as documented in Section 4.3.

There are two patterns we document that are inconsistent with at least a standard employer-driven taste-based discrimination model. First, the convergence in the racial composition of hires with cumulative hires holds *within establishment*. A model where employer tastes over employee race are fixed would not generate this result.

Second, a standard taste-based discrimination model would not generate the finding that there are racial differences in dismissal rates that dissipate with cumulative hires. If racially biased employers set a lower threshold for dismissing hires from their disfavored group, then a forward-looking employer would account for this preference at the hiring stage and set a more demanding threshold for hiring job seekers from that group. It may be possible to rationalize this pattern with a more complicated taste-based model where decision-makers that make hiring and firing decisions are different and misaligned (Lehmann, 2013).

There is also a sense in which taste-based discrimination may play an implicit role in our model. Incumbent employees have discretion over which job seekers to refer, and over which social connections to form in the first place.

5.3 Complementarities in Production

A third alternative explanation is that workers are more productive when their co-workers are of the same race (Lang, 1986). Complementarities in production would naturally lead to workplace segregation. The racial composition of hires could converge across firms if these complementarities are stronger among early employees.

Without productivity data, this explanation is difficult to rule out. However, it is not clear why this mechanism would generate the racial differences in dismissal rates that we observe.

5.4 Worker Preferences

A fourth interpretation is that it reflects job seeker preferences over workplace characteristics. In particular, nonwhite job seekers prefer to not work at small or young employers with white founders. To evaluate this alternative hypothesis, we build on the insight that, under some assumptions, worker preferences over employers can be inferred from worker mobility patterns (e.g., Sorkin, 2018).

There are now several approaches to constructing a revealed preference ranking of employers. We use the *poaching rank* as developed by Bagger and Lentz (2018). The premise of the poaching rank is that higher-ranked employers should hire relatively more workers from employment than from unemployment. That’s because poaching a worker from another employer indicates that the worker prefers the destination employer. The poaching index for establishment J is defined as the share of all new hires that are poached from other employers:

$$p_J = \frac{n(., J)}{n(0, J) + n(., J)} \quad (10)$$

where $n(., J)$ is number of hires poached from other and $n(0, J)$ hires from unemployment. The poaching rank of establishment J is a conversion of the poaching index into an ordinal ranking of employers. We present more details on the construction of the poaching rank in Section B.1.

In the Appendix B we examine how race-specific poaching indices vary with founder race and total hires (see Appendix Figure B.10). We do not find evidence that nonwhite job seekers prefer to not work at small or young employers with white founders.

6 Implications for Racial Inequality

We have documented evidence that, on average, employers screen job seekers with more precision when they share the founder’s racial background. This advantage in screening precision is declining in an employer’s cumulative hires and size. We also discuss in Section 3 that entrepreneurship rates for white adults are twice as high as the same rates for nonwhite adults in Brazil. In combination with our findings, this suggests that referral hiring will disadvantage nonwhite job seekers in the aggregate (for example, see Bolte et al., 2020). Moreover, racial disparities in entrepreneurship are not limited to Brazil. In the United States, about 13% of the adult population was black in 2012, while only 2% of businesses with at least one paid employee were black-owned (Camara et al., 2019).

In this section we argue that the dynamic effects of referral hiring, combined with racial differences in entrepreneurship, can help explain three stylized facts about racial differences in labor market outcomes. First, nonwhite workers are more likely to be dismissed by their employers than white workers. Second, nonwhite workers have less seniority than their white coworkers on average. Third, nonwhite workers sort to larger employers than white workers.

6.1 Dismissal Rates

In our sample, 17.3% and 15.1% of nonwhite and white hires are dismissed within 90 days of their start date. In the United States, black workers are more likely than white workers to be laid off, fired, or discharged (Cavounidis et al., 2021). In the context of our model, these racial differences in “involuntary” separations could be explained by the fact that nonwhite or black hires are less likely to be referral hires.

To assess whether referral hiring can explain aggregate differences in dismissal rates, we compare dismissal rates in firms with white and nonwhite founders. We document in Section 4.5 that, within firms with white founders, white hires are less likely to be dismissed than nonwhite hires. The opposite is true for firms with nonwhite founders, though the magnitude of racial differences in dismissal rates are smaller. Here we conduct a similar but distinct exercise. While in Section 4.5 we measure *within-firm* gaps in dismissal rates, coinciding with our employer-level model and model predictions, here we pool firms and combine both within-firm and between-firm variation in dismissals.

We estimate the following model, separately for all entrant firms, firms with white founders, and firms with nonwhite founders:

$$\log(E(\text{DISMISSED-3M}_{it}|\cdot)) = \tau_t + \omega_{o(i,t)} + \beta \text{NONWHITE}_i + \epsilon_{it}. \quad (11)$$

Estimates for equation (11) are presented in Panel A of Table 5. Columns 1 through 3 pool all entrant firms, columns 4 through 6 limits to firms with white founders, and columns 7 through 9 limit to firms with nonwhite founders. Columns 1, 4, and 7 include only year fixed effects as additional controls; columns 2, 5, and 8 include year fixed effects and occupation fixed effects; columns 3, 6, and 9 include year fixed effects and education fixed effects. For all establishments pooled, nonwhite hires are dismissed at an elevated rate. Without adjusting for job or worker characteristics (column 1), nonwhite hires are about 8% more likely to be dismissed within 3 months. This declines to 4% or 8% with the inclusion of occupation or education fixed effects.

These differences are driven primarily by firms with white founders, where nonwhite hires are 8%–12% more likely to be dismissed, depending on the specification. By contrast, at establishments with nonwhite founders, nonwhite hires are 1% to 4% more likely to be dismissed.

[Table 5 about here.]

6.2 Seniority

Buhai et al. (2014) find that separation rates are decreasing and wages are increasing in *seniority*, defined as worker’s tenure relative to the tenure of their colleagues. Our model as written does not have substantive predictions for seniority because we ignore quits. However, the logic of the model suggests that nonwhite employees at establishments with white founders will tend to have less seniority than their white coworkers because they are hired later in an establishment’s life-cycle.

Following Buhai et al. (2014), we define a worker’s *seniority index* as follows. Define q_{ijt} as the number of workers in establishment j with tenure greater than or equal to tenure of worker i at time t . Define n_{jt} as the total number of workers in establishment j at time t . The seniority index is defined as

$$\log r_{ijt} \equiv \log n_{jt} - \log q_{ijt}. \quad (12)$$

We estimate the following linear model, separately for all entrant firms, firms with white founders, and firms with nonwhite founders:

$$\log r_{ijt} = \tau_t + \omega_{o(i,t)} + \beta \text{NONWHITE}_i + \nu \log n_{jt} + \epsilon_{it}. \quad (13)$$

Estimates for equation (13) are presented in Panel B of Table 5. Columns 1 through 3 pool all entrant firms, columns 4 through 6 limits to firms with white founders, and columns 7 through 9 limit to firms with nonwhite founders.

Overall, nonwhite employees have 4% to 5% less seniority than white employees. This is driven by firms with white founders, where nonwhite employees have 9% to 10% less seniority. At firms with nonwhite founders, nonwhite and white employees have similar seniority on average.

6.3 Employer Size

Referral hiring can explain a striking pattern present in both Brazil and the United States that has received little attention: nonwhite and black workers sort to larger employers (Holzer, 1998; Miller, 2017). The sorting of nonwhite and black workers to large employers is perhaps surprising given that (1) large employers tend to pay more and employ more educated workers (Brown and Medoff, 1989) and (2) nonwhite workers tend to work at lower-paying firms, at least in Brazil (Gerard et al., forthcoming). We show that other observable job characteristics cannot explain this sorting pattern.

To characterize the relationship between the racial composition of new hires and establishment size, we estimate models of the form

$$\log(E(\text{NONWHITE}_{it}|\cdot)) = \sigma_{c(J(i,t))} + \tau_t + \mu_{m(J(i,t))} + \omega_{o(i,t)} + \epsilon_{it} \quad (14)$$

where each observation is a new hire, i indexes workers, t indexes time, and $J(i,t)$ indexes the establishment. $\sigma_{c(J(i,t))}$ are fixed effects for the establishment’s size category, τ_t are year fixed effects, $\mu_{m(J(i,t))}$ are microregion (local labor market) fixed effects, and $\omega_{o(i,t)}$ are fixed effects for combinations of occupation, industry, and worker education. Establishment size is measured as of December 31 in the year of the hire.

The estimated $\sigma_{c(J(i,t))}$ coefficients for various specifications of equation (14) are presented in Figure 5. The omitted category is establishments with 1-4 employees. The first specification includes only year fixed effects as additional explanatory variables. The coefficient of 0.044 for establishments with 5-9 employees indicates that the nonwhite share of hires is 4.4 log points (4.5%)

larger at establishments with 5-9 employees relative to establishments with 1-4 employees. Coefficients are monotonically increasing in establishment size. The coefficient is 0.351 for establishments with 1,000 or more employees, indicating that the nonwhite share of hires is 42.0% larger at these establishments relative to establishments with 1-4 employees.

[Figure 5 about here.]

We increase the saturation of the model with each specification. The second specification includes microregion fixed effects, to little effect. Large establishments are not disproportionately concentrated in local labor markets with large nonwhite populations. The third specification includes 3-digit occupation by 2-digit industry fixed effects. These fixed effects are rich characterizations of jobs; they explain 52% of variation in starting log wages. Including occupation by industry fixed effects reduces the magnitude of the size effects moderately. For example, the coefficient for establishments with 1,000 or more employees declines from 0.351 to 0.249. But a robust size gradient remains. The fourth specification replaces occupation by industry fixed effects with occupation by industry *by worker education* fixed effects, where worker education is divided into three categories: less than high school education, high school graduate, and college graduate. Incorporating education slightly *increases* the magnitude of the $\sigma_{c(J(i,t))}$ coefficients.

We conclude that nonwhite workers sort to larger establishments and that this pattern cannot be explained by other job characteristics potentially correlated with size, including location, occupation, industry, and educational requirements.

7 Conclusion

We present a simple job search model with referral hiring, test its predictions using administrative data from Brazil, and consider its consequences for racial inequality. We emphasize the implications of referral hiring for how the racial composition of an employer’s hires varies: (1) with the race of the founder; (2) over time; and (3) with the employer’s size. Among other predictions of the model, we confirm that (a) firms with white and nonwhite founders are more likely to hire white and nonwhite employees; (b) these differences disappear as establishments’ cumulative number of hires increases; (c) firms are less likely to dismiss recent hires of the same race as the founder; and (d) racial differences in dismissal rates are also decreasing in an establishment’s cumulative number of hires.

Given substantial racial disparities in entrepreneurship rates, the widespread practice of referral hiring appears to disadvantage nonwhite workers (relative to white workers) in the aggregate. We document some implications for racial inequality in match quality. A natural open question is what implications these the combination of referral hiring and racial differences in entrepreneurship have for racial inequality in wages and employment rates.

Our findings suggest that market frictions that affect the size distribution of firms will have implications for racial inequality in the labor market (Restuccia and Rogerson, 2017). For example,

if small, productive firms are unable to expand to their efficient size due to some resource misallocation, these firms are also less likely to reach the point of having a racially diverse workforce. The logic of our findings suggests that the aggregate costs of misallocation will be disproportionately borne by groups underrepresented among entrepreneurs. On the other hand, dynamic markets with high firm turnover may also disadvantage groups underrepresented among entrepreneurs if firms that reach the scale needed to employ a diverse workforce make up a small share of the market.

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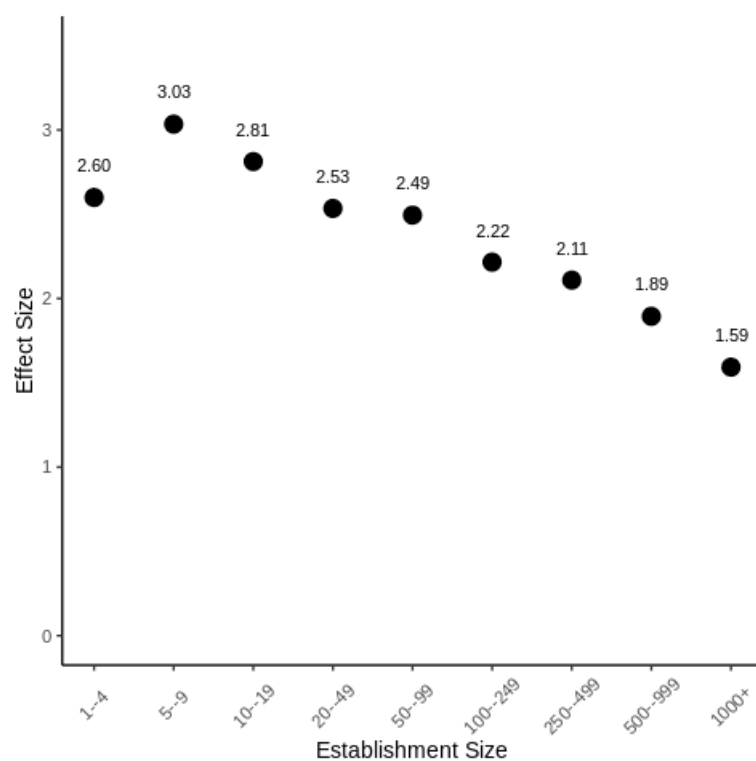
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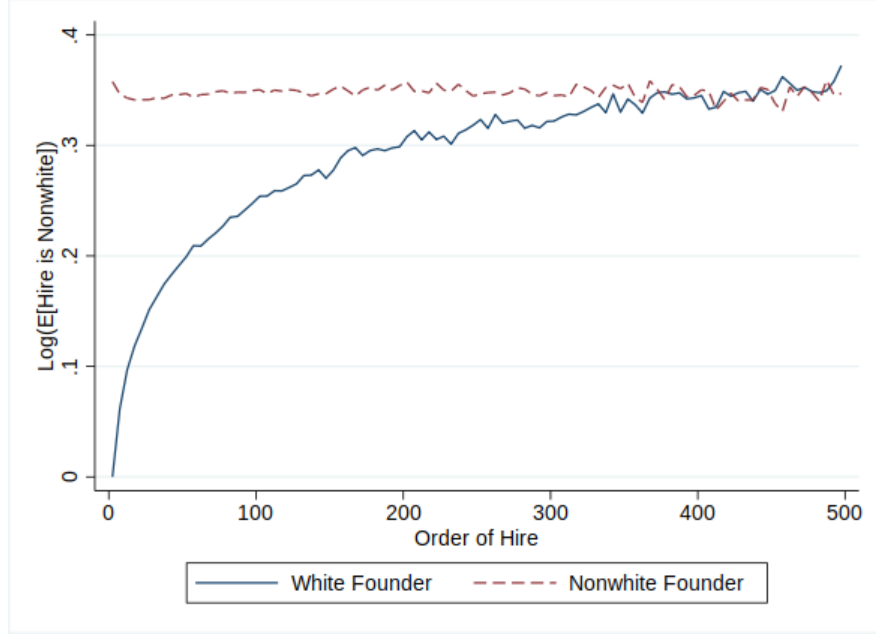
FIGURE 1
REFERRAL EFFECTS DECREASING IN ESTABLISHMENT SIZE



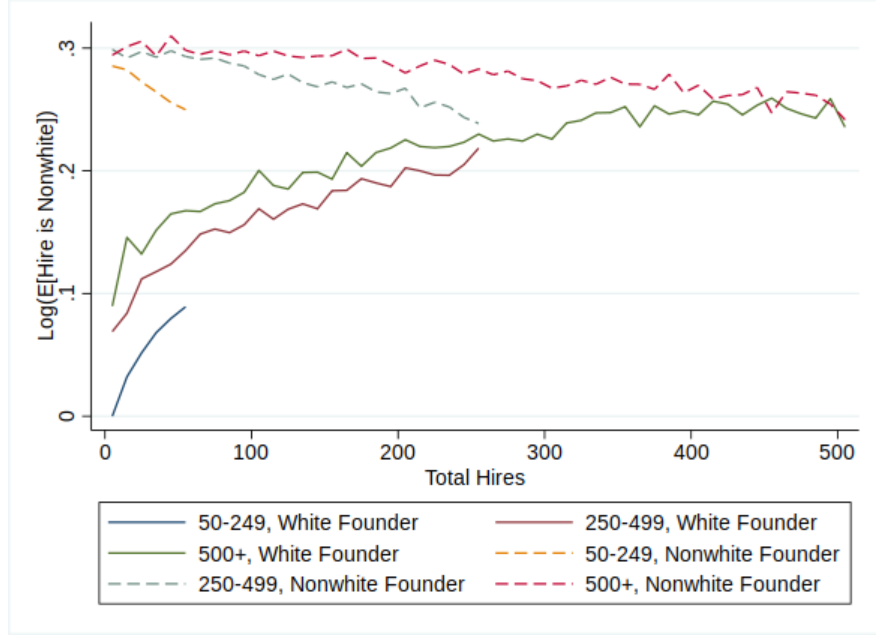
Note: This figure plots point estimates of referral effects by destination establishment size from estimating equation (2). The plotted coefficients represent the proportional increase in the probability a job seeker is hired at a destination plant when a linked past coworker is present relative to the case where no linked past coworker is present.

FIGURE 2
NONWHITE SHARE OF HIRES CONVERGES WITH CUMULATIVE HIRES

(a) Pooled

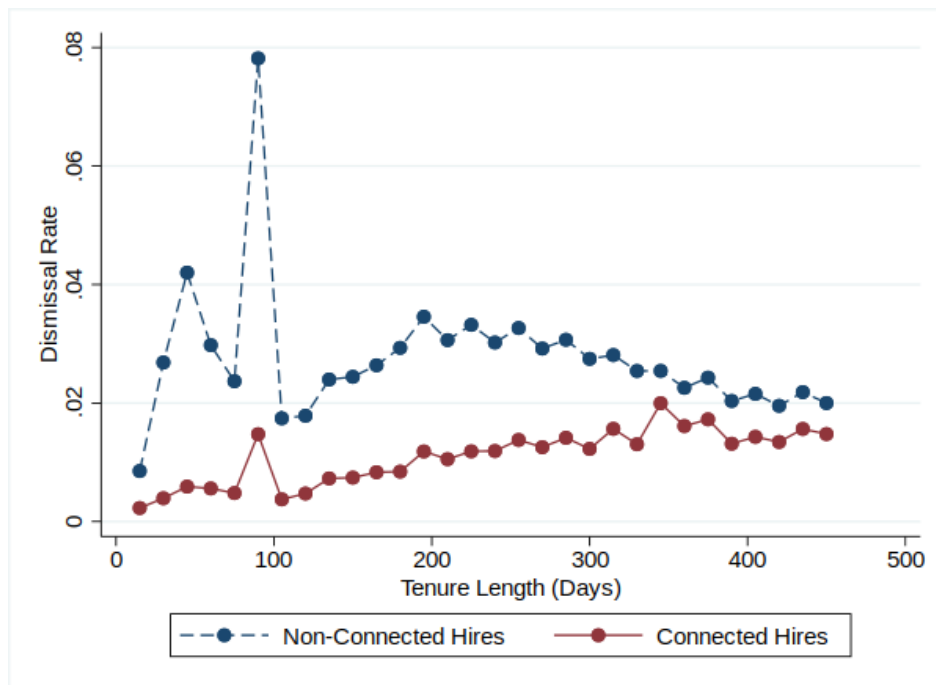


(b) By Total Hires, Balanced



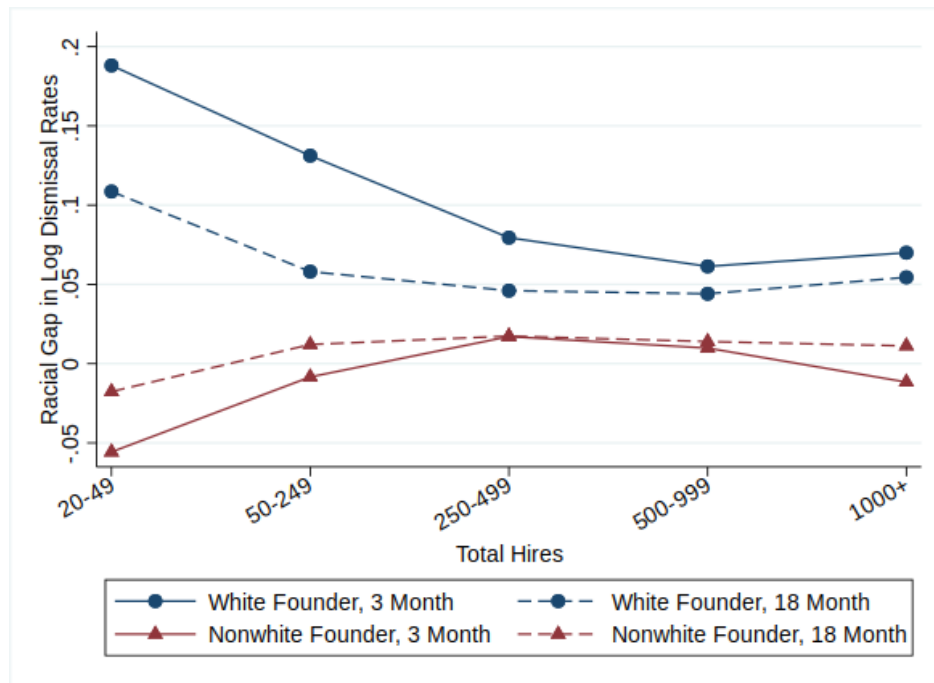
Note: This figure plots the relationship between the racial composition of a firm's hires and its cumulative hires to date. Panel A plots the $\eta^{n,r}$ coefficient estimates from equation (4), summarizing the relationship between a firm's racial composition of hires, its cumulative hires to date (n), and the race of its founder (r). Panel B plots the $\eta^{s,n,r}$ coefficient estimates from equation (5), which allows the relationship between a firm's racial composition of hires, its cumulative hires to date, and the race of the founder to vary with the firm's total observed hires (s). Both models are estimated via Poisson quasi maximum likelihood (PQML). In Panel A the omitted category is the first five hires after the year of entry for firms with white founders. In Panel B the omitted category is the first ten hires after the year of entry for firms with white founders and 50-249 total observed hires. Founder race is inferred from the race of the top-paid manager or employee at entry.

FIGURE 3
DISMISSAL RATES BY CONNECTED STATUS OVER TENURE



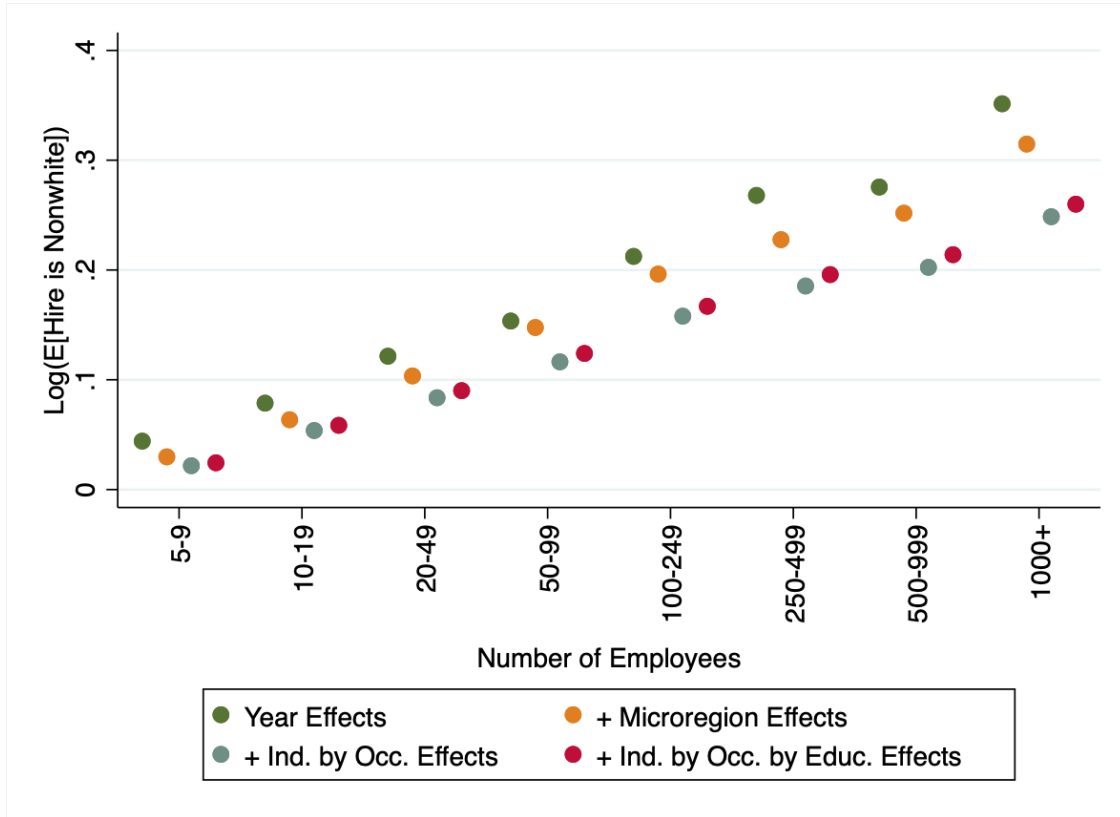
Note: This figure plots dismissal rates by job spell tenure for connected and non-connected hires, adjusting for establishment, occupation, and year fixed effects as described in equation (6). The model is estimated via Poisson quasi maximum likelihood (PQML). “Connected” hires had previously shared a workplace (with no more than 100 employees) with an incumbent at this establishment.

FIGURE 4
RACIAL DISPARITY IN DISMISSAL RATES BY TOTAL HIRES



Note: This figure plots the adjusted, firm-level nonwhite-white difference in log dismissal rates as a function of founder race and the firm's total number of observed hires after the year of entry. Firm-specific racial differences in dismissal rates are constructed as described in equation (8). The model is estimated via Poisson quasi maximum likelihood (PQML). We limit to establishments with 20 or more hires.

FIGURE 5
NONWHITE SHARE OF NEW HIRES BY ESTABLISHMENT SIZE



Note: This figure plots $\sigma_{c(J(i,t))}$ coefficient estimates for several specifications of the model (14) described in Section 6.3, which are estimated via Poisson quasi maximum likelihood (PQML). *Year Effects* refers to a model that includes only year effects (τ_t) as additional controls. *+ Microregion Effects* refers to a model that includes microregion fixed effects ($\mu_{m(J(i,t))}$) in addition to year effects. *+ Ind. by Occ. Effects* refers to a model that also includes fixed effects for 3-digit occupation by 2-digit industry combinations. *+ Ind. by Occ. by Educ. Effects* replaces industry by occupation fixed effects with fixed effects for industry by occupation by worker education category fixed effects.

TABLE 1
ENTREPRENEURSHIP RATES AND CHARACTERISTICS OF PRIVATE
SECTOR EMPLOYEES BY RACE GROUP

	All (1)	White (2)	Mixed (3)	Black (4)
A: Men				
Share of sample in column race group	1.00	0.48	0.43	0.08
Share in private employment	0.42	0.44	0.40	0.47
Share entrepreneurs	0.033	0.044	0.022	0.019
<i>Characteristics of private sector employees</i>				
Share in formal sector employment	0.78	0.82	0.75	0.78
A: Women				
Share of sample in column race group	1.00	0.50	0.41	0.08
Share in private employment	0.22	0.26	0.18	0.21
Share entrepreneurs	0.017	0.024	0.011	0.008
<i>Characteristics of private sector employees</i>				
Share in formal sector employment	0.80	0.82	0.76	0.80

This table reports statistics from the Pesquisa Nacional por Amostra de Domicílios (PNAD) household survey for the years 2002 through 2014. The sample is limited to men and women of ages 18 to 65. We define entrepreneurs as those that self-report running a business with at least one paid employee.

TABLE 2
RAW DIFFERENCES IN WORKER AND JOB CHARACTERISTICS BY RACE

	All Employees			Recent Hires					
				All Firms			Entrant Firms		
	Pooled (1)	White (2)	Nonwhite (3)	Pooled (4)	White (5)	Nonwhite (6)	Pooled (7)	White (8)	Nonwhite (9)
Nonwhite (%)	36.5	0.0	100.0	39.0	0.0	100.0	36.0	0.0	100.0
Log Wage	2.006 (0.674)	2.079 (0.713)	1.878 (0.581)	1.851 (0.553)	1.900 (0.582)	1.775 (0.493)	1.840 (0.455)	1.877 (0.468)	1.777 (0.421)
Male (%)	66.3	64.3	69.9	67.4	64.8	71.4	65.5	63.4	69.3
Age	33.7	34.0	33.1	30.9	31.1	30.7	31.0	31.2	30.7
< HS	30.4	28.7	33.5	28.4	25.9	32.3	21.5	19.6	24.8
HS Grad	57.2	56.3	58.8	61.7	61.8	61.4	69.5	69.7	69.1
College Grad	12.4	15.0	7.7	9.9	12.2	6.3	9.1	10.7	6.0
Number of Worker-Year Obs.	688m	437m	251m	254m	155m	99m	55m	35m	20m

This table reports summary statistics from the *Relação Anual de Informações Sociais* (RAIS) data for the years 2003-2017. We limit the sample to the jobs of men and women between the ages of 18 and 65 on private sector, indeterminate length contracts for at least 30 hours per week. Columns (1)-(3) report statistics for all job spell-years. Columns (4)-(9) report statistics for the first year of a job spell. Columns (7)-(9) restrict to entrant firms as described in Section 4.3.

TABLE 3
DESCRIPTIVE STATISTICS FOR REFERRAL ANALYSIS
SAMPLE

	Hired	Connections	Dyads
White	0.319	0.486	0.302
Male	0.576	0.644	0.489
Age	31.204	33.78	30.97
Linked			0.072
Dest. Size			
1–99	58.2	59.3	59.4%
100–499	21.4	20.9	21.7%
500+	20.4	19.8	18.9%
Num. Obs.	1,450,133	4,462,676	118,291,395

Source: RAIS, 2003–2017. The ‘Dyads’ column includes pairs of hired workers matched to potential origin destinations. The ‘Hired’ column describes the hired workers; the ‘Connections’ column describes the incumbent workers that are linked to some hired worker via a past co-working relationship.

TABLE 4
REFERRAL EFFECTS BY ESTABLISHMENT SIZE AND RACE

	Overall		Size Group		Race Match
	(1)	(1-99) (2)	(100-499) (3)	(500+) (4)	(5)
Linked	0.622 (0.014)	1.035 (0.029)	0.766 (0.031)	0.492 (0.020)	
<i>Effect Size</i>	<i>1.863</i>	<i>2.815</i>	<i>2.15</i>	<i>1.635</i>	
Race Match (Seeker / Incumbent)					
Nonwhite / Nonwhite					0.715 (0.018)
Nonwhite / White					0.282 (0.030)
White / Nonwhite					0.070 (0.029)
White / White					0.843 (0.026)
Estab. Pair FE	✓	✓	✓	✓	✓
Pseudo R ²	0.432	0.489	0.451	0.410	0.433
Num. Obs.	2,159,225	211,743	375,833	1,528,293	2,159,225

This table presents estimated referral effects from equations (1) (columns 1 through 4) and (3) (column 5) described in Section 4.1. The effect size reported is the exponentiated value of the coefficient, and measures the relative increase in the probability of a hire when a coworker link is present relative to case where one is not.

TABLE 5
RACIAL DIFFERENCES IN DISMISSAL RATES AND JOB SENIORITY, BY FOUNDER RACE

	All Entrants			White Founders			Nonwhite Founders		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A									
<i>Outcome: Dismissal During Probation</i>									
Nonwhite	0.083 (0.001)	0.042 (0.001)	0.075 (0.001)	0.121 (0.001)	0.081 (0.001)	0.114 (0.001)	0.042 (0.001)	0.011 (0.001)	0.036 (0.001)
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
Occupation FEs		✓			✓			✓	
Education FEs			✓			✓			✓
Number of Obs.		52,376,661			35,138,895			17,237,766	
Panel B									
<i>Outcome: Seniority Index</i>									
Nonwhite	-0.049 (0.000)	-0.040 (0.000)	-0.050 (0.000)	-0.097 (0.000)	-0.086 (0.000)	-0.099 (0.000)	0.002 (0.000)	0.005 (0.000)	0.000 (0.000)
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
Occupation FEs		✓			✓			✓	
Education FEs			✓			✓			✓
Number of Obs.		39,203,654			26,171,760			13,031,894	

This table presents regression coefficient estimates for equation (11) in Panel A and equation (13) in Panel B. In Panel A the outcome is an indicator for whether a job spell results in a dismissal within 3 months of the hire date. Each observation is a job spell. In Panel B the outcome is the *seniority index*, which summarizes an employee's tenure relative to their colleagues, and is defined in equation (12). Each observation is a job spell-year. Columns 1 through 3 pool all entrant firms, columns 4 through 6 limits to firms with white founders, and columns 7 through 9 limit to firms with nonwhite founders.

ONLINE APPENDIX: THE DYNAMICS OF REFERRAL HIRING AND RACIAL INEQUALITY: EVIDENCE FROM BRAZIL

CONRAD MILLER

IAN SCHMUTTE

JULY 2021

A Data Appendix

A.1 RAIS Data

To prepare the RAIS data, we take several steps. First, we clean the raw data files retrieved from the MTE. Next, we prepare a master dataset that imposes certain variable definition and data cleaning decisions. Finally, we prepare various samples that are needed for particular analyses.

A.1.1 Cleaning the Raw Data

The raw data files are delivered by year, and our analysis in this paper uses the data from 2003–2017. The variables available change across years, as does their coding. In a first step, we build a codebook and redefine variable names and labels to better track relationships among the variables.

Workers are uniquely identified by a PIS code and establishments by a CNPJ code. From there, we build a relational database comprised of four tables:

- ‘Job’ table with a single record for each PIS-CNPJ-YEAR that includes all characteristics specific to the employment match
- ‘Establishment’ table with a single record for each CNPJ-YEAR pair with all characteristics specific to an establishment
- ‘Worker’ table, with a single record for each PIS

To prepare the Job table, we must first disambiguate a handful of records that duplicate the same PIS-CNPJ pair in some year. In the raw data, for each year the data record one observation for each statutory employment relationship between a worker and an establishment.

In a small fraction (less than 2 percent) of cases, the data have multiple records for the same PIS-CNPJ pair in a given year. A negligible number (around 15 per year out of roughly 60 million) also share the same reported date of hire. The vast majority (95-98 percent) are pairs with exactly 2 records in the same year. The extra records are associated with administrative reassignments that are not consequential for our analysis, and mostly occur in public-sector jobs. In all cases,

we combine the repeated records into a single PIS-CNPJ-level record that includes all earnings information, the earliest date of hire, and all other characteristics from the record with the latest date of separation. We implement the disambiguation described above so that each record is uniquely identified by a combination of PIS-CNPJ-YEAR. For variables whose coding changes over time (like education and race), we define a harmonized version that has a consistent coding across all years. To prepare the ‘Establishment’ table, we compute the modal value for each establishment characteristic (industry, size class, location, ownership type) across all job-level records in the ‘Jobs’ table. The ‘Worker’ table includes the modal values for race, gender, and date of birth across all job-level observations and across all years that involve the same PIS.

An important feature of the RAIS data is that establishments can, and do, report different values for the demographic characteristics of the same PIS. We therefore retain the time-varying information on employer-reported race, gender, date of birth, and education in the ‘Job’ table. We do define an additional measure of education which records, for each year, the highest level of education reported for that PIS up to that date.

A.1.2 Primary Analysis Data

From the cleaned database, we extract primary analysis data for each of Brazil’s five regions. We impose very few restrictions at this stage, but define a number of key variables:

Wages: the real hourly wage (in 2015 Brazilian Reais). We divide real monthly earnings by the number of contracted hours per month. To approximate the number of hours a worker is contracted to work each month, we multiply contracted hours per week, which is reported in RAIS, by $\frac{30}{7}$. Average monthly earnings are reported in nominal reais, which we convert to constant 2015 reais using the OECD’s Consumer Price Index for Brazil (?).

Dominant Job: In much of the literature, and our analysis, it is common to assemble a worker-year panel from the linked data. Since workers often hold multiple jobs in the same year, we define the *dominant job* as the job with highest earnings for the year among all those with the longest observed tenure.

Valid Identifiers: The PIS and CNPJ numbers are social security and tax identifiers that include check digits, by which it is possible to identify records with invalid identifiers.

A.1.3 Data for Referral Analysis

For the analysis of referrals, we first extract data on new hires from the primary analysis data. We restrict the sample to dominant jobs for observations with valid PIS and CNPJ identifiers. The RAIS data provide several different ways to identify new hires, and we require they all agree. Specifically, we extract PIS-CNPJ-YEAR observations when they are (1) the first time this PIS-CNPJ is observed; (2) the match is actually coded as a new hire; (3) the recorded year of hire corresponds to the year of the observation.

For each new hire, defined above, we link information on their prior year employer, including those who were not employed in the prior year.

To define coworking relationships, we first extract all observations with valid CNPJ and PIS data for 2003–2015, keeping only full-time jobs (at least 35 hours contracted per week) and in establishments with at least 4 and fewer than 100 employees. We then produce a dataset of coworking pairs that records all pairs of workers (PIS codes) that were employed in an overlapping window working in the same occupation and in the same establishment.

To build the referral dyads, we first associate each worker hired in a given year t with the plant from which they separated in year $t - 1$. The analysis in the paper is based on dyads constructed using data from 2013–2017. From this data, we are able to define the set of all origin firms and, for each origin firm, the set of all potential destinations. As discussed in the main text, we only need to worry about potential destinations for which at least one separating worker from the plant moves. So, for each separating worker, we assign one observation for each potential destination. Then, using the information on past coworking pairs, we define “linked” potential destinations as those where the separating worker has a prior coworking relationship with at least one incumbent worker. Finally, we link basic demographic information for the focal (separating) worker and for the linked incumbent (when there is one).

To ensure that our analysis of referrals is not simply picking up tied moves where multiple workers from the same plant all move to the same destination, we do several things. First, we ensure that the linked incumbent in the potential destination was not hired in the same year the separating worker is at risk to move there. Second, we only use coworking relationships that were formed at least two years prior to the move. Finally, we make sure that the plant at which the two workers were most recently employed together was neither the origin firm for the separating worker, nor the potential destination where the linked incumbent is employed.

For our analysis of dismissals, we also define for each year a list of all newly hired workers that indicates whether they have a past coworking history with any incumbent worker at their new establishment.

B Appendix: Additional Results

B.1 Racial Differences in Preferences over Employer Size

One alternative explanation for the sorting pattern we document is that, relative to white job seekers, nonwhite job seekers have a strong preference for working at large employers. We build on the insight that, under some assumptions, worker preferences over employers can be inferred from worker mobility patterns (e.g. Sorkin, 2018). We use the *poaching rank* as developed by Bagger and Lentz (2018). The premise of the poaching rank is that higher-ranked employers should hire relatively more workers from employment than from unemployment. That’s because poaching a worker from another employer indicates that the worker prefers the destination employer. The poaching index for establishment J is defined as the share of all new hires that are poached from

other employers:

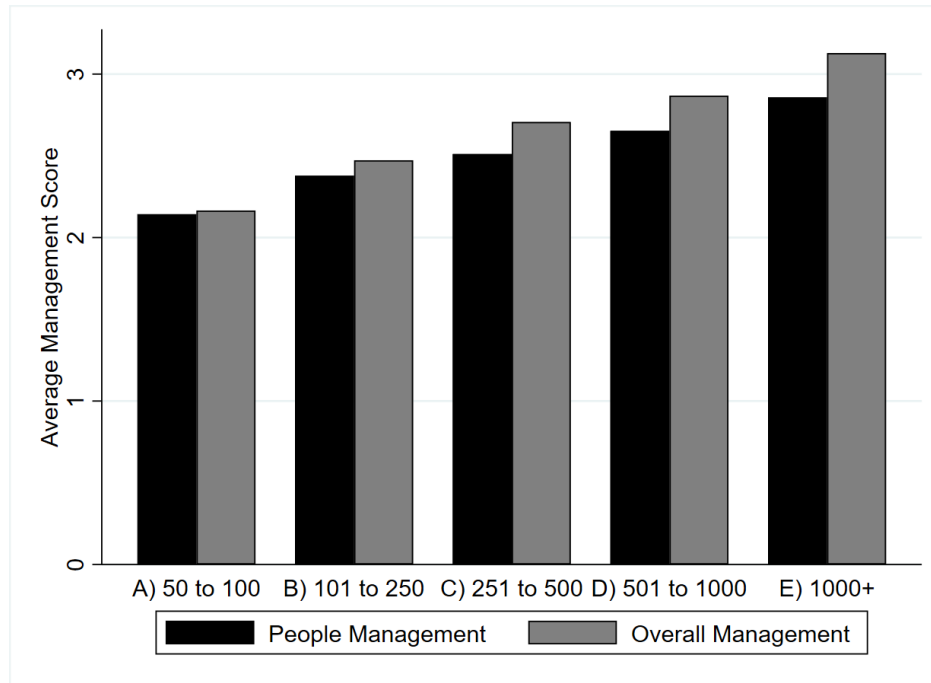
$$p_J = \frac{n(., J)}{n(0, J) + n(., J)} \quad (\text{B.1})$$

where $n(., J)$ is number of hires poached from other and $n(0, J)$ hires from unemployment.

The poaching rank of establishment J is simply a conversion of the poaching index into an ordinal ranking of employers. We group establishments into 1000 quantiles based on their poaching index.

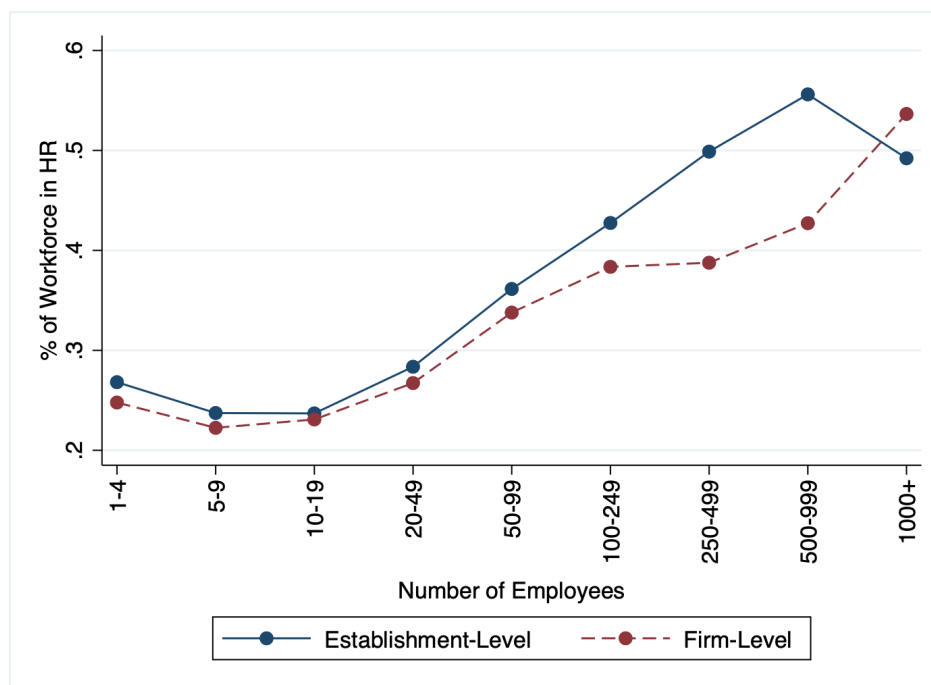
We measure race-specific poaching ranks for each establishment, and then relate those ranks to founder race and total hires using the sample of entrants discussed in Section 4.3. Figure B.10 reports the results.

FIGURE B.1
WORLD MANAGEMENT SURVEY SCORES INCREASING IN EMPLOYER SIZE



Note: This figure reports average overall management and people management scores for medium and large Brazilian manufacturing firms in the World Management Survey. The scores measure the adoption of formal management practices in different areas of performance, including personnel (people) management, operations, and target-setting. See Bloom et al. (2014).

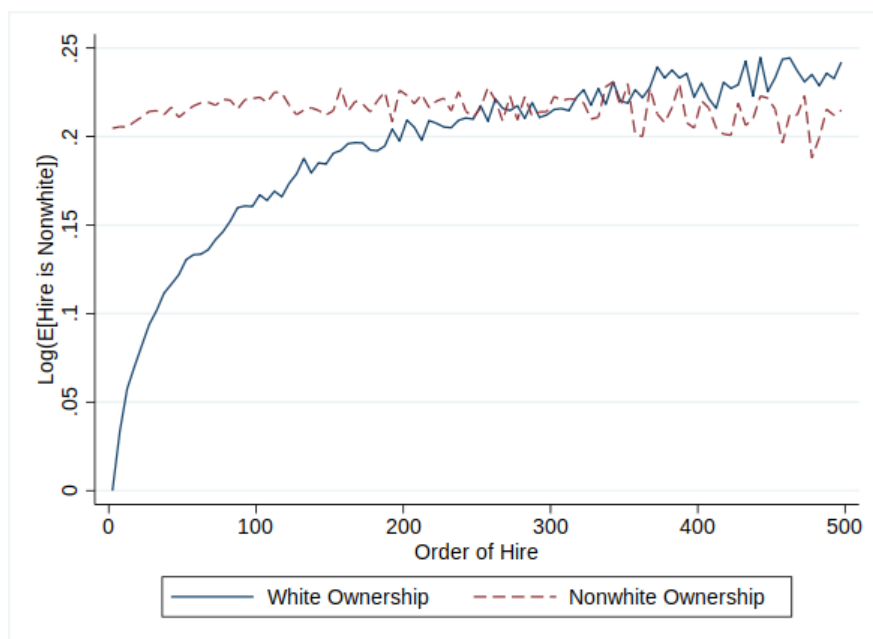
FIGURE B.2
SHARE OF WORKFORCE IN HUMAN RESOURCES INCREASING IN EMPLOYER SIZE



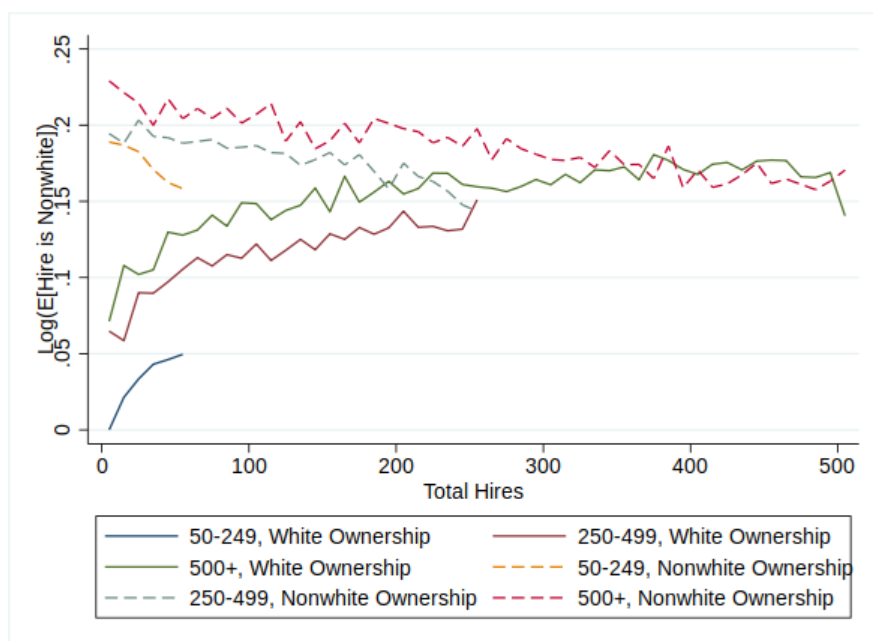
Note: This figure reports the share of an employer's workforce in human resources-related (HR) occupations. HR occupations include: *administrador* (administrator); *diretor de recursos humanos* (human resources director); *gerente de recursos humanos* (human resources manager); and *gerente de departamento pessoal* (personal department manager). The HR share is calculated for each plant by year combination, then averaged across plant by year combinations weighting by number of hires.

FIGURE B.3
NONWHITE SHARE OF HIRES CONVERGES WITH CUMULATIVE HIRES, BY OWNERSHIP

(a) Pooled

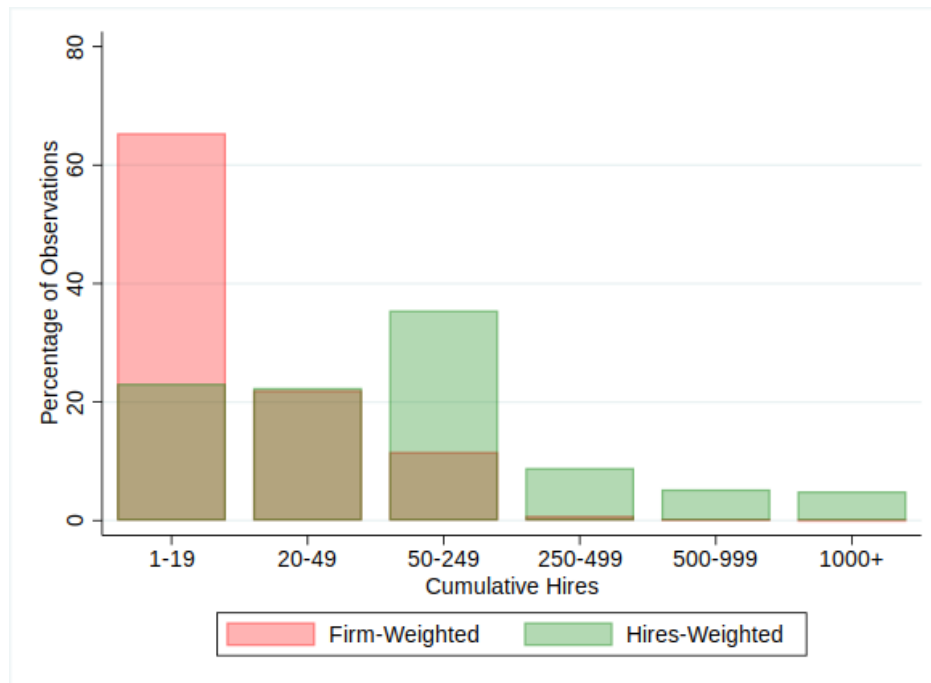


(b) By Total Hires, Balanced



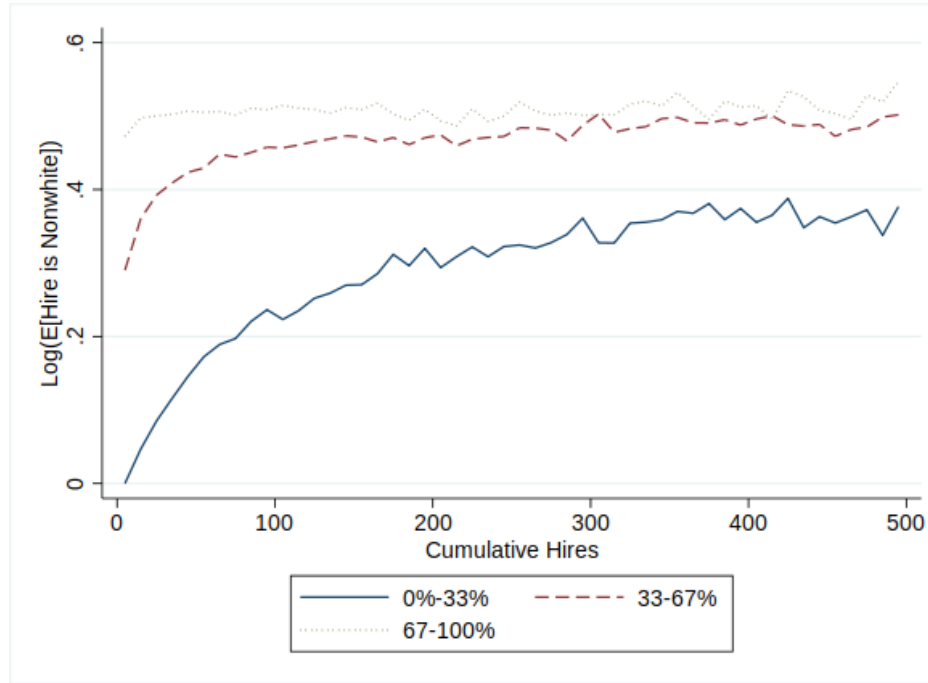
Note: This figure plots the relationship between the racial composition of a firm's hires and its cumulative hires to date. Panel A plots the $\eta^{n,r}$ coefficient estimates from equation (4), summarizing the relationship between a firm's racial composition of hires, its cumulative hires to date (n), and the race of its founder (r). Panel B plots the $\eta^{s,n,r}$ coefficient estimates from equation (5), which allows the relationship between a firm's racial composition of hires, its cumulative hires to date, and the race of the founder to vary with the firm's total observed hires (s). Both models are estimated via Poisson quasi maximum likelihood (PQML). In Panel A the omitted category is the first five hires after the year of entry for firms with white founders. In Panel B the omitted category is the first ten hires after the year of entry for firms with white founders and 50-249 total observed hires. Founder race is inferred from the racial composition of the firm's ownership.

FIGURE B.4
CUMULATIVE HIRES DISTRIBUTION 5 YEARS POST-ENTRY



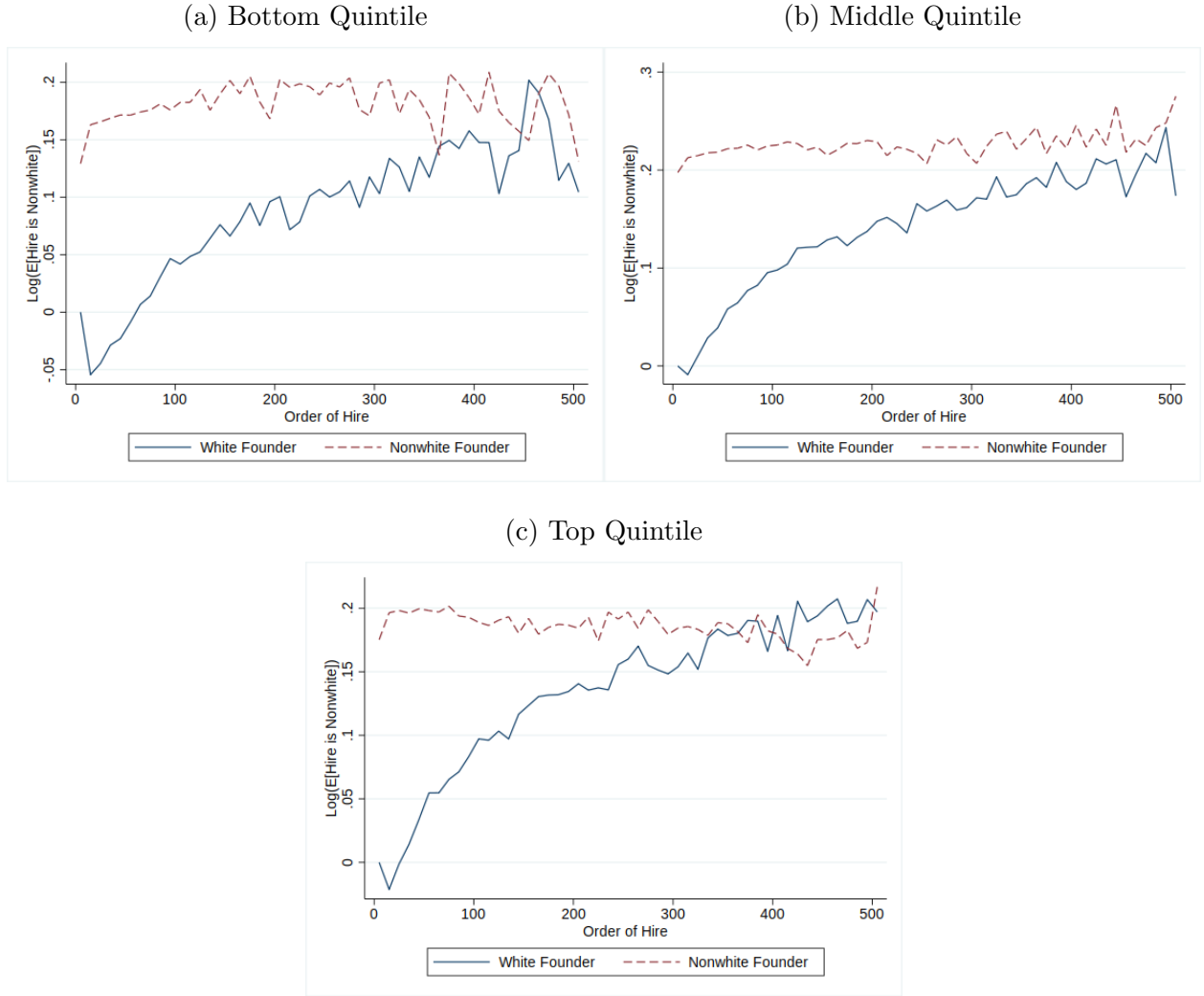
Note: This figure plots a histogram for the number of cumulative hires by firms 5 years after entry. The sample is limited to firms that remain in the RAIS data 5 years after entry. In the ‘Firm-Weighted’ bars, each firm is weighted equally. In the ‘Hires-Weighted’ bars, each firm is weighted by their number of cumulative hires.

FIGURE B.5
NONWHITE SHARE OF HIRES CONVERGES WITH CUMULATIVE HIRES, NEW ESTABLISHMENTS
OF EXISTING FIRMS



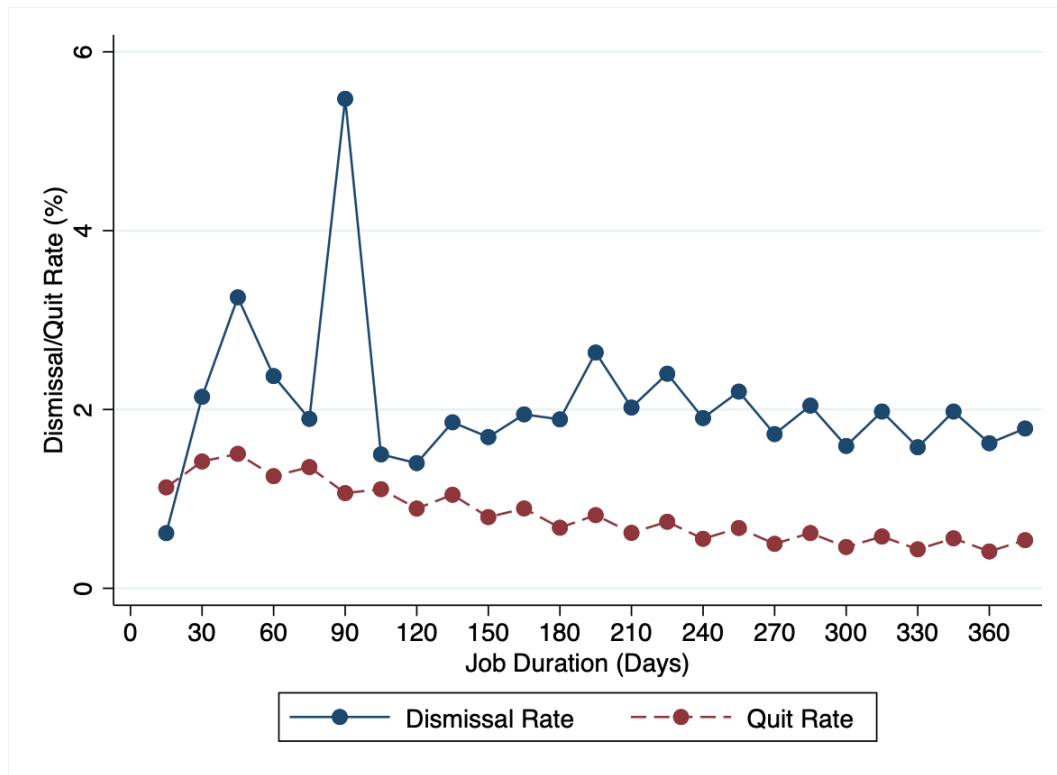
Note: This figure plots the relationship between the racial composition of an entrant establishment's hires and its cumulative hires to date. The figure plots the $\eta^{n,r}$ coefficient estimates from equation (4), summarizing the relationship between an establishment's racial composition of hires, its cumulative hires to date (n), and the racial of employees at incumbent establishments in the firm (r). The model is estimated via Poisson quasi maximum likelihood (PQML). The omitted category is the first five hires after the year of entry for firms with white founders. We characterize establishments by the racial composition of the firm's incumbent employees, and divide establishments into three categories on this basis: 0-33%, 33-67%, and 67-100%.

FIGURE B.6
NONWHITE SHARE OF HIRES BY CUMULATIVE HIRES FOR VARYING FIRM PAY PREMIUMS



Note: This figure plots the $\eta^{n,r}$ coefficient estimates from equation (4), summarizing the relationship between an establishment's racial composition of hires, its cumulative hires to date (n) and the race of its founder (r). The model is estimated via Poisson quasi maximum likelihood (PQML). In each panel the omitted category is the first hire of establishments with white founders.

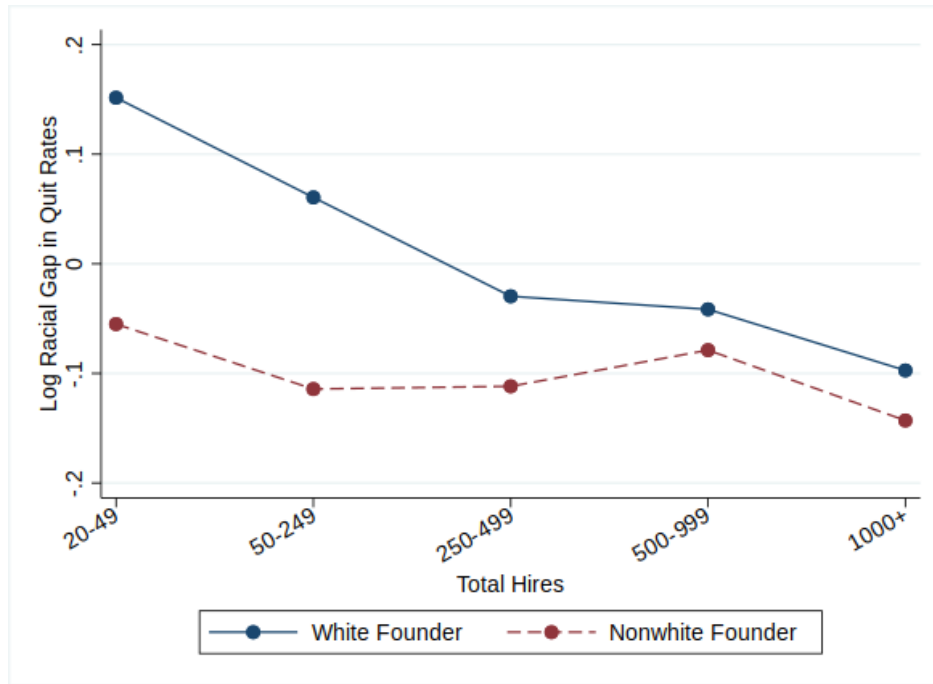
FIGURE B.7
DISMISSAL AND QUIT RATES BY JOB TENURE



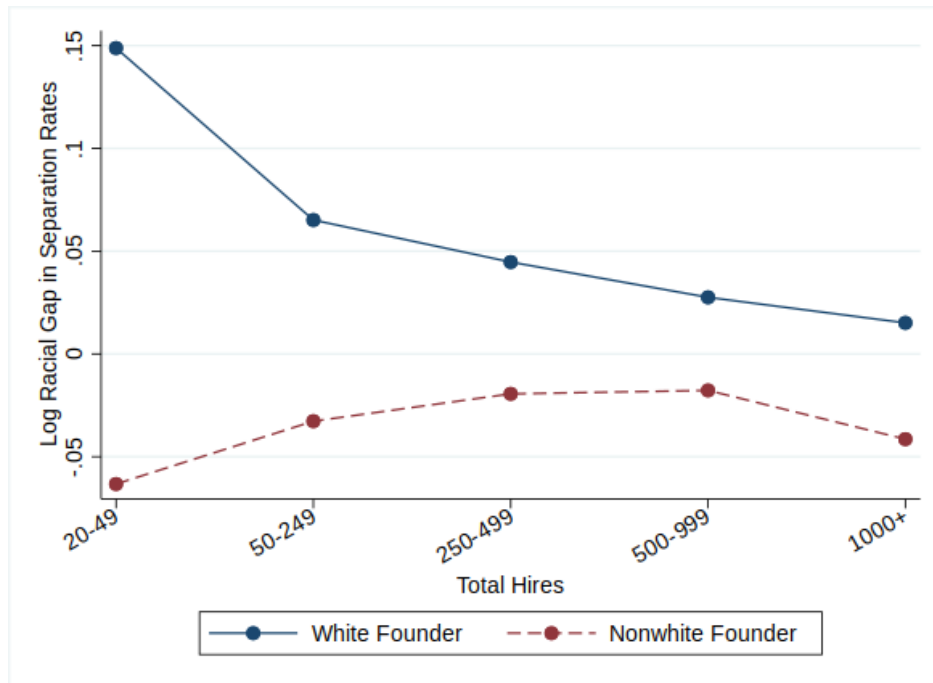
Note: This figure presents dismissal (or employer-initiated or ‘involuntary’ separations) and quit (or employee-initiated separation) hazard rates as a function of job spell tenure. Tenure is grouped in 15 day periods.

FIGURE B.8
RACIAL DISPARITY IN QUIT AND SEPARATION RATES BY TOTAL HIRES

(a) Quits

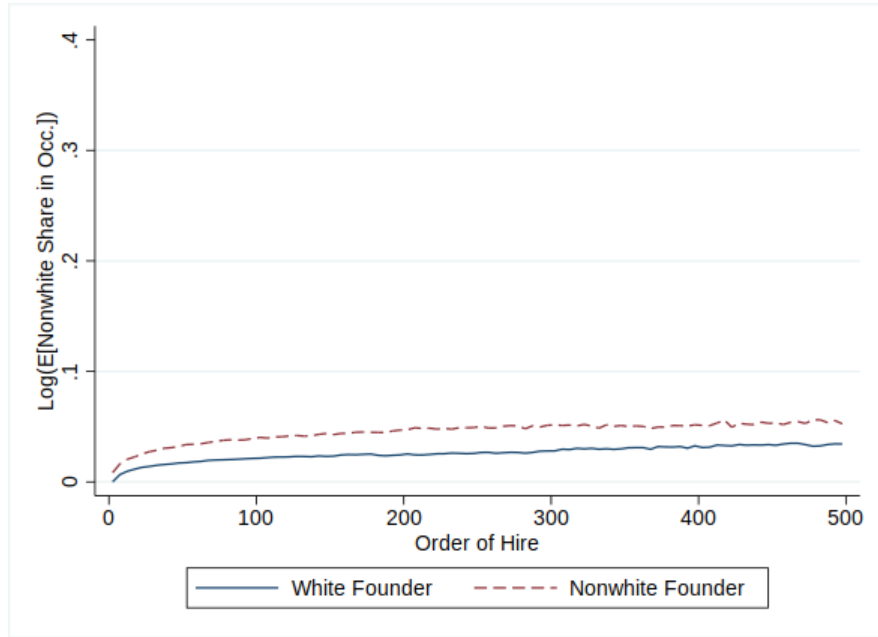


(b) Separations



Note: These figure plot the adjusted, establishment-level nonwhite-white difference in log quit rates (Panel A) and separation rates (Panel B) as a function of founder race and the establishment's total number of observed hires after the year of entry. Establishment-specific racial differences in quit and separation rates are constructed as described in equation (8). The model is estimated via Poisson quasi maximum likelihood (PQML). We limit to establishments with 20 or more hires.

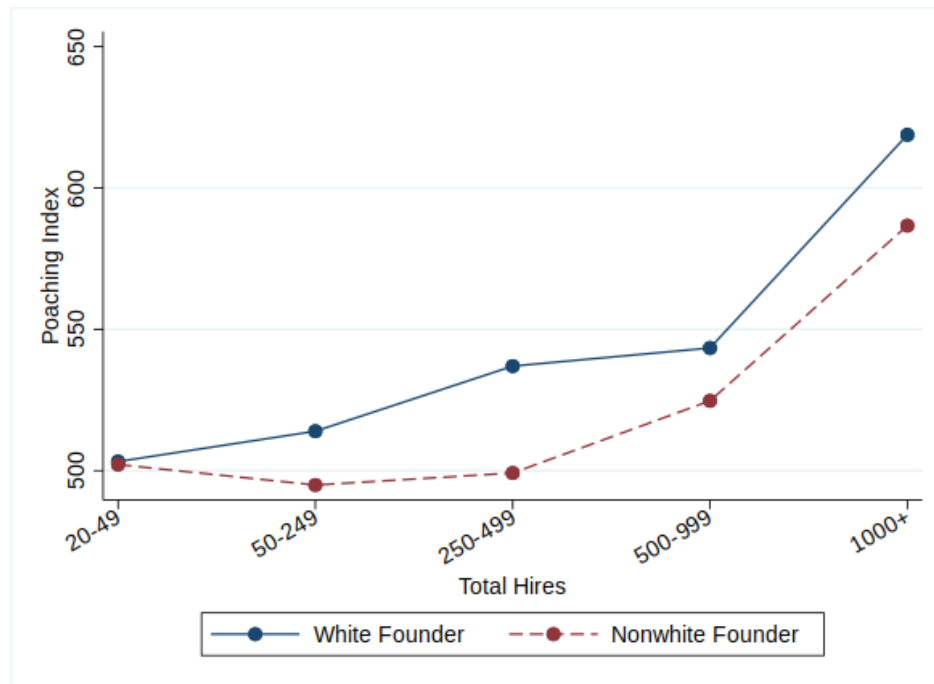
FIGURE B.9
OCCUPATION-BASED PREDICTED NONWHITE SHARE WITH CUMULATIVE HIRES



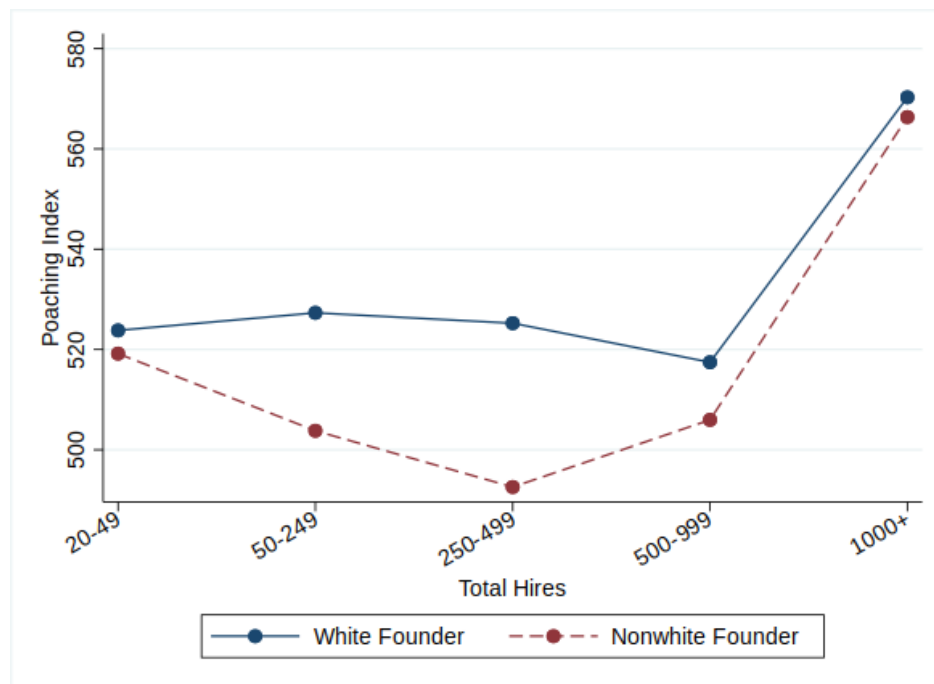
Note: This figure plots the relationship between the racial composition of a firm's hires and its cumulative hires to date. The figure plots the $\eta^{n,r}$ coefficient estimates from equation (4), summarizing the relationship between a firm's racial composition of hires, its cumulative hires to date (n), and the race of its founder (r). The omitted category is the first five hires after the year of entry for firms with white founders. Founder race is inferred from the race of the top-paid manager or employee at entry.

FIGURE B.10
POACHING INDEX BY FOUNDER RACE AND TOTAL HIRES

(a) White Hires



(b) Nonwhite Hires



Note: This figure reports race-specific average poaching ranks by an establishment's total hires and founder's race. The same of entrant establishments is described in Section 4.3. The poaching rank is defined in Section B.1.

TABLE B.1
CHARACTERISTICS OF ENTRANT ESTABLISHMENTS

	Pooled Founders (1)	White Founders (2)	Nonwhite Founders (3)
Nonwhite Founder (%)	33.0	0.0	100.0
<i>Persistence</i>			
After 3 Years	65.5	66.4	63.8
After 5 Years	42.3	43.3	40.2
<i>Total Hires</i>			
After 3 Years			
1-19	79.2	79.4	79.0
20-49	14.3	14.3	14.4
50-249	6.1	6.0	6.2
250-499	0.3	0.3	0.4
500-999	0.1	0.1	0.1
1000+	0.0	0.0	0.0
After 5 Years			
1-19	65.4	65.6	64.8
20-49	22.0	21.8	22.4
50-249	11.6	11.6	11.6
250-499	0.8	0.8	0.9
500-999	0.2	0.2	0.3
1000+	0.1	0.1	0.1
Number of Firms	2.27m	1.52m	0.75m

This table reports summary statistics for entrant establishments in the *Relação Anual de Informações Sociais* (RAIS) data for the years 2003-2017.

TABLE B.2
CHARACTERISTICS OF ENTRANT ESTABLISHMENTS, BY
OWNERSHIP

	Pooled Founders (1)	White Founders (2)	Nonwhite Founders (3)
Nonwhite Founder (%)	18.0	0.0	100.0
<i>Persistence</i>			
After 3 Years	65.4	65.9	63.0
After 5 Years	42.3	43.0	39.1
<i>Total Hires</i>			
After 3 Years			
1-19	74.8	75.2	73.3
20-49	16.9	16.9	17.3
50-249	7.7	7.5	8.6
250-499	0.4	0.4	0.6
500-999	0.1	0.1	0.1
1000+	0.0	0.0	0.0
After 5 Years			
1-19	59.5	59.9	57.4
20-49	24.7	24.6	25.5
50-249	14.3	14.1	15.1
250-499	1.1	1.0	1.4
500-999	0.3	0.3	0.5
1000+	0.1	0.1	0.2
Number of Firms	1010k	829k	181k

This table reports summary statistics for entrant establishments in the *Relação Anual de Informações Sociais* (RAIS) data for the years 2003-2017.

TABLE B.3
REFERRAL HOMOPHILY BY FOUNDER RACE

Founder Race	Southeast		South		Northeast	
	White (1)	Nonwhite (2)	White (3)	Nonwhite (4)	White (5)	Nonwhite (6)
Nonwhite / Nonwhite	0.789 (0.087)	0.814 (0.166)	0.926 (0.057)	0.932 (0.165)	0.468 (0.074)	0.627 (0.047)
Nonwhite / White	0.292 (0.112)	0.560 (0.218)	0.330 (0.058)	0.628 (0.202)	0.187 (0.143)	0.393 (0.131)
White / Nonwhite	0.284 (0.117)	0.400 (0.212)	0.413 (0.068)	0.722 (0.227)	0.648 (0.178)	0.252 (0.103)
White / White	0.822 (0.090)	0.915 (0.203)	0.9663 (0.041)	0.667 (0.170)	1.202 (0.151)	1.068 (0.136)
Estab. Pair FE	✓	✓	✓	✓	✓	✓
Pseudo R ²	0.441	0.495	0.450	0.401	0.433	0.397
Num. Obs.	57,086	26,909	131,887	5,623	25,745	48,640

This table shows differences in the importance of racial homophily for referrals by the race of the firm's founder. We report results separately for the Southeast, South, and Northeast regions of Brazil.

TABLE B.4
DISMISSAL RATES BY CONNECTED STATUS

	(1)	(2)	(3)	(4)
Connected	-1.889 (0.014)	-1.890 (0.014)	-1.759 (0.014)	-1.751 (0.014)
Year FEs	✓	✓	✓	✓
Occupation FEs		✓		✓
Establishment FEs			✓	✓
Number of Obs.	20,476,890			

This table presents regression coefficient estimates for equation (7). The outcome is an indicator for whether a job spell results in a dismissal within 3 months of the hire date. Each observation is a job spell.