Access to Financing and Racial Pay Gap Inside Firms*

Janet Gao
Georgetown University
janet.gao@georgetown.edu

Wenting Ma
UMass Amherst
wentingma@umass.edu

Qiping Xu
UIUC
qipingxu@illinois.edu

Abstract

We examine how firms' access to financing affects the racial pay gap inside firms using granular data on worker earnings and career histories. Exploiting exogenous shocks to firms' debt capacity, we find that better access to financing significantly narrows racial pay gaps inside firms, especially among higher-skilled workers, firms with worse diversity practices, and in tighter labor markets. Following the shocks, minority workers are more likely to be promoted and reassigned to technology-oriented occupations. Our evidence is consistent with financing-induced labor demand improving firms' utilization of minority workers' human capital, generating long-lasting gains for minority workers.

Keywords: Racial Inequality, Diversity, Promotion, Financing Friction, Access to Debt.

JEL classification: J31, J71, G3.

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1 Introduction

Firms' ability to access credit markets is a crucial driver of labor demand and job growth (Chodorow-Reich, 2014; Duygan-Bump et al., 2015; Falato and Liang, 2016; Benmelech et al., 2019; Ersahin, 2020). Easier access to financing enables firms to expand employment, allocate human capital to more productive tasks, and raise worker compensation (Hombert and Matray 2017; Bai et al. 2018; Popov and Rocholl 2018). However, the gains from growth are not evenly distributed among workers (Beck et al. 2010; Moser et al. 2023). An important question arises as to whether workers from disadvantaged populations, such as minority races, benefit more or less compared to their peers during the phase of fast growth. While the prior literature link financial development to regional racial inequality (Levine, 2013), much less is known about how finance shapes racial inequality inside corporations, and the specific mechanisms underlying such effects.

We study how firms' access to debt markets affects the pay gap between White and minority workers within firms. Racial pay gap is a persistent phenomenon in many economies and remain a focus of policy interest. As of 2021, White workers in the U.S. earned about 14% more than non-White workers (McKinney et al., 2022). While part of the racial pay gap reflects worker-firm sorting (i.e., between-firm pay gap), much originates from firm-specific practices (i.e., within-firm pay gap) (Altonji and Blank 1999; Heywood and Parent 2012; Gerard et al. 2021). Research shows that minority workers face substantial within-firm barriers such as occupational segregation, lack of mentorship, promotion biases, among others.[1]

How does firms' access to financing affect the racial pay gap? The answer is not obvious. On the one hand, finance-driven labor demand may counteract the labor market frictions faced by minority workers, thus reducing the racial pay gap. On the other hand,

[1]Many studies, such as Elvira and Town (2001), Castilla (2008), Lahey and Oxley (2021), Miller and Schmutte (2021), Tripp and Fadlon (2020), Kline et al. (2022) explore within-firm frictions that contribute to racial income gaps, including biased performance evaluation, different promotion rates, social connections among workers and firms, or simply homophily. Other studies also document that substantial segregation and occupational stratification at the workplace, where minority workers are assigned to lower-paid or lower-ranked occupations, contributing to the racial pay gap inside firms (Penner, 2008; Giuliano et al., 2009; Åslund et al., 2014). Practitioner reports often cite worker-task sorting and the lack of mentorship as key barriers to minority advancement (Dobbin and Kalev, 2016; Smith, 2022). Ferreira and Pikulina (2023) builds a theoretical framework linking firm productivity, discrimination, and incentives for human capital investment across demographic groups.

gains from finance-driven production growth may be disproportionately captured by the incumbent majority, aggravating the racial pay gap. This could happen if the pre-existing frictions against minority workers are overwhelmingly strong, or if skilled workers are abundant across both demographic groups. It is also possible that financing has little effect on racial inequality if firms face similar frictions in hiring across demographics.

We develop a simple theoretical framework to illustrate the forces at play. The model describes the labor allocation decisions of a "biased" firm, which prioritizes White workers for skilled tasks. A better access to debt markets leads to a growing demand for talent. With skilled White workers in limited supply, the firm increasingly allocates minority workers to fill the expansion. This sets minority workers onto better career trajectories, raises their compensation, and ultimately reduces the racial pay gap. Ultimately, the impact of financial access on the racial pay gap remains an empirical question.

To answer this question, we exploit exogenous shocks to firms' access to debt markets and utilize granular data on worker earnings and career paths. We find evidence consistent with the first hypothesis: improved access to financing reduces the racial pay gap within firms. Following a positive shock to debt financing, minority workers experience greater wage growth, become more likely to be promoted to higher-paid positions, and are increasingly reallocated to technology-oriented occupations compared to their White coworkers.

Using data from the U.S. Census Bureau and Revelio Labs, we construct employer-employee matched panels to track workers' earnings, job positions, locations, and demographic information. We first document a sizable racial earnings gap in U.S. public firms, widening from 10.4% to 16.5% between 1990 and 2012. The gap persists after controlling for education, sex, tenure, and firm-year fixed effects, suggesting it is not driven by observable characteristics or worker-firm sorting. Even within-occupations, minority workers hold fewer senior, high-paying positions, receive fewer promotions, and experience lower mobility, contributing to the observed racial earnings gap.

We seek causal inferences regarding the effect of access to financing using the staggered introduction of anti-recharacterization laws (ARLs). ARLs strengthened the protection of creditors' rights by facilitating their seizure of collateral assets during bankruptcy proceedings and increased lenders' willingness to extend credit outside of bankruptcy. Consequently, the laws allowed firms to raise more debt, potentially from different markets and at lower costs (Li et al. 2016; Ersahin 2020; Favara et al. 2021). ARLs were enacted in a staggered fashion across several U.S. states from the late 1990s to the early 2000s, and affected firms incorporated in those states while their workers often operate outside their states of incorporation.[2] Our identification strategy compares individuals with similar characteristics working in the same state, whose employers face similar local labor market conditions but differ only in whether they are incorporated in an ARL-adopting state. This design isolates idiosyncratic firm-level shocks to financing that affect the racial pay gap and internal labor allocation. Crucially, our sample does not include workers physically working in the ARL-adoption states, mitigating concerns that concurrent local policy changes drive our results.

We adopt a triple-difference-in-difference design in a stacked event sample, comparing changes in real earnings of White and minority workers in matched treated and control firms around the passage of ARLs. Following the passage of ARLs, the within-firm racial pay gap shrinks by around 3 percentage points in affected firms relative to workers in control firms operating in the same industry, location, and time. The significant reduction is consistent with minority workers having substantially higher labor supply elasticities than White workers (Bartik, 2008). As a redult, for firms with growing labor demand, raising the pay to attract minority workers is likely more cost-effective than raising the pay for White workers.

This finding is robust to the control of firm-by-worker fixed effects and firm-by-year fixed effects, which purge away the influence of firm-worker sorting and any firm-level characteristics. Thus, we only contrast the earnings of minority and White workers at the same firm. Moreover, we find a 2-percentile increase in minority workers' within-firm pay rank, suggesting that minority workers are advancing into higher job ranks. This evidence also alleviates concerns that our results are driven by specific measures of pay gaps or by rising earnings dispersion across job ranks (Bayer and Charles, 2018).

Separating minorities into Black, Asian, and other races, we find that the pay gap exists for both Black and Asian workers relative to White workers, and firms' better access

[2] 71% of publicly listed firms within Compustat operate their businesses outside their incorporation states during 1990-2017.

to financing narrows the gap similarly for both races. Further analyses show that the effects are concentrated among minority men and are not driven by minority immigrants.

In a dynamic setting, we show that the pay gap between White and minority workers remains stable prior to the adoption of ARLs but declines substantially afterward. Earnings of both groups are flat in the pre-event years and gradually rise following the shock, but the earnings of minority workers increase significantly more than those of White workers, leading to a narrowing pay gap.

Through what mechanisms does better access to financing reduce the racial pay gap within firms? We consider several possibilities. We start with the observation that minority workers are disproportionately matched to less senior, lower-paying positions inside firms. This pattern is consistent with both academic and anecdotal evidence that minority workers are assigned lower-ranked positions or worse-fitting tasks than White workers, due to frictions such as biased beliefs, management-workers social connections, and psychological dissonance.[3]

There are at least two channels through which the financing shocks we study could increase minority workers' pay. First, the shocks may increase the return to minority-dominated job categories, which are typically lower-skill and lower-paid. Under this mechanism, among minority workers, lower-skill individuals should be more affected by firms' access to financing. Second, the shocks may lead firms to better utilize and develop minority workers' human capital. Prior research documents that the adoption of ARLs leads firms to expand, adopt new technology, and innovate more (Mann, 2018; Ersahin, 2020). Expansion increases task complexity and raises the demand for skilled labor. Facing a limited skilled labor supply, firms may allocate higher-skill tasks to minority employees whose human capital was previously under-utilized.[4] This could lead to an increase in

[3]Prior studies documents that minority workers tend to occupy lower ranked positions compared to White workers despite possessing similar skills. Golan et al. (2019) find that black workers are assigned to less complex tasks than White workers in their early careers, leading to persistent income differentials. Gui (2021) finds that minority staffers are more likely to be assigned to lower-ranked positions with fewer promotion chances. Social skills and referral relationships could also lead to different chances of promotion between White and minority workers (Fadlon, 2021). Through randomized field experiments, Cohen et al. (2006) find that the racial achievement gap could be partially explained by the psychological threat of confirming a negative stereotype when seeing certain racial groups make achievements.

[4]For example, firms can provide mentorship and training to develop minority workers' human capital, promote them to more senior roles, or reassign them to positions better aligned with their skills.

minority workers' compensation. This "human capital utilization" mechanism suggests that skilled minority workers should experience larger gains following financing shocks.

To distinguish these two mechanisms, we investigate the heterogeneous effects across worker skill levels. Using education and pre-event earnings as proxies for skill, we find that the effects of ARLs are more pronounced for mid- and high-skill workers. Following the enactment of the laws, the racial pay gap decreases by 4.6 percentage points among workers with above high-school education, and 4 percentage points among workers whose pre-event income falls into the middle and top terciles. In contrast, the racial pay gap barely changes among workers without high-school education and among low-income workers. These results are consistent with the human capital utilization channel.

To further substantiate the human capital utilization channel, we track the career trajectories of minority and White workers using Revelio resume data across several dimensions of within-firm career progression. Within our sample, on average, minority workers have lower likelihoods of job mobility and promotion rates across all the above dimensions than White workers. However, these racial gaps diminish when firms gain improved access to debt markets. Following the adoption of the ARLs, minority workers experience significantly greater increases in within-firm job mobility and promotion rates –by about 40% and 60% relative to sample means, respectively–compared to White workers. They are also more likely to transition into a tech-oriented occupation. In sum, these results provide textured evidence regarding *how* firms' access to financing improves the career advancement of skilled minority workers.

The human capital utilization channel requires there to be pre-existing biases or frictions inside the firms preventing minority workers from matching to better-suited tasks. We verify this condition by examining heterogeneity in effects across firms with different degrees of pre-existing racial inequality or workplace norms. We find the reduction in the racial pay gap to be more pronounced at firms where White workers earned higher premiums over minority workers prior to the shocks, and among firms with less diverse boards of directors. These patterns suggest that minority workers faced greater barriers to advancement and to accessing better career opportunities before the shocks.[5]

Finally, we document that our effects become stronger in commuting zones with higher unemployment rates, and with a lower employment share of White workers. In these labor markets, employers potentially face worker shortages, especially White workers, and may rely more on minority workers to meet elevated labor demand.

Collectively, findings from the above analysis suggest that our effects are unlikely driven by White and minority workers having different skills or education, or by time-varying premiums for low-skill tasks. Instead, they are consistent with the idea that the finance-induced labor demand makes employers overcome pre-existing labor frictions and allocate more minority workers to productive tasks.

Thus far, our analysis has focuses on the "incumbent" workers who remain in the firm. We next examine the extensive margin, investigating whether the expansion of firms' debt capacity affects worker turnover and the earnings of newly hired employees. While improved access to financing reduces separation rates for the average worker, there is no differential change between White and minority workers, alleviating concerns that our findings may be driven by dynamic selection between workers and firms. At the same time, we document a 6.2-percentage-point reduction in the pay gap between newly hired White and minority workers after ARLs, suggeesting that under pressure to meet growing hiring needs, firms offer more equitable pay to attract minority workers.

How do minority workers fare in the long run? When minority workers switch jobs, does the external labor market undo their earnings gain from firm-specific financing shocks? Using U.S. Census administrative data, we track treated workers throughout their employment histories and find no evidence that the racial pay gap reverts to pre-event levels after job changes. Instead, minority workers continue to earn higher incomes after switching employers. Two factors may explain this persistence. First, minority workers may have received better opportunities or training in affected firms, leading to permanent

[5]For example, based on Becker's theory, managers, including board members, tend to select workers based on their taste and discriminate against other races (Becker, 1971; Giuliano et al., 2009). When managerial positions are predominantly occupied by White workers, White workers are more likely to be hired or promoted than minority workers. Consistently, Bernile et al. (2018) and Cai et al. (2022) show that firms with more diverse boards are associated with a more diverse workforce.

human capital improvements. Second, wage increases or promotions within treated firms may have raised outside firms' pay offers to attract these workers. Overall, our analysis suggests that relaxing financing frictions has durable effects on minority workers' earnings.

We assess the external validity of our findings using an alternative setting where firms face external financing constraints. Specifically, we compare firms with more or less short-term debt due at the onset of the Global Financial Crisis (GFC). Since the GFC was largely unanticipated (Cheng et al., 2014) and triggerred a sharp rise in borrowing costs (Duchin et al., 2010; Krishnamurthy, 2010), firms with more debt due faced greater refinancing difficulties and tighter external financing constraints–conditions extensively used in prior research as exogenous financing shocks (Duchin et al., 2010; Almeida et al., 2011; Carvalho, 2015). We find that minority workers in firms with more debt due experienced significantly slower wage growth than White workers, although effects on promotion gaps are muted. This evidence complements our baseline findings and highlights the critical role of firms' credit access in shaping racial inequality among workers.

Our study contributes to several strands of literature. First, it adds to the research on racial wage gaps. A large body of literature documents the existence, trends, and determinants of the racial wage gap in the U.S. and other economies (see Altonji and Blank (1999) for a review). Most of the literature focuses on labor market frictions and, relatedly, the sorting of workers to firms, skills, and tasks. Recent work suggests that firm policies and characteristics play an important role in shaping racial inequality (e.g., Carrington and Troske 1998; Miller and Schmutte 2021; Gerard et al. 2021). Yet, there is little evidence on how financial frictions faced by employers affect the racial pay gap. Using granular employee-employer matched data, we add to this literature by providing evidence that firms' access to debt markets significantly reduces the earnings gap between White and non-White workers inside firms.

Relatedly, our findings complement two studies examining the effect of financial shocks on income inequality in a locality. Levine (2013) show that banking deregulation is followed by reduced racial inequality in a state.[6] Beck and Levkov (2010) document

[6]The mechanisms documented in Levine (2013) differ significantly from the ones in our study. Levine (2013) find that banking deregulation leads to more firm entry, which strengthens local labor market

that bank deregulation tightened the income distribution by increasing the relative wage rates of unskilled workers. Avenancio-León and Shen (2021) find that credit expansion associated with banking deregulation is associated with a reduced gender pay gap in certain industries. Unlike these studies, we do not look at aggregate shocks at the state level, but instead focus on idiosyncratic, firm-specific shocks and compare affected firms to unaffected ones operating in the same state and industry. This approach allows us to isolate the role of firms in moderating the racial pay gap, and purge away potential confounding effects related to labor supply or economic conditions at the local level.

Our study also contributes to the growing literature on the effects of financial markets on corporate ESG performance (Xu and Kim 2022; Houston and Shan 2022). Studies in this literature document that access to financing helps improve firms' environmental policies and ESG ratings. We add to this literature by showing that better access to debt financing helps improve racial equity, i.e., the "S" dimension of ESG performance. More importantly, we provide evidence shedding light on the mechanisms leading to this effect.

2 Conceptual Framework

We provide a simple model to illustrate the intuition behind the prediction that access to financing can influence the racial pay gap within firms. The model is purposely kept sparse to demonstrate key mechanisms. We present the model setup and conclusion here, leaving the details to Internet Appendix I.

This is a one-period model involving one firm's decision to allocate workers to positions/tasks at time t. After job allocation is done, production starts. The firm distributes all profit as dividends and is dissolved in $t + 1$. To finance its production, the firm uses its internal resources N (i.e., net worth) and borrows D. The cost of debt financing is R, assumed to be fixed in a competitive credit market.

There are two tasks inside the firm, a skilled task (Task 1) and an unskilled task (Task

competition and raises minority pay. Li (2022) examines the role of banking deregulation in affecting entrepreneurial gaps. Howell and Brown (2022) document incumbent and new-hire workers inside small, private firms benefit differently from a cash windfall. Instead, we show that better access to financing improves the promotion opportunities and the skill-position matching for minority workers.

2). For simplicity, we assume each task only requires human capital input: L_1 and L_2. The firm's production follows the standard CES function $(\alpha L_1^\rho + \beta L_2^\rho)^{1/\rho}$, where $\rho \leq 1$ and $0 < \beta < \alpha < 1$. Thus, Task 1 is more productive for the firm than Task 2.

The firm can utilize White or minority workers for either task. We denote the amount of White (minority) workers performing Task 1 as $l_1^{(w)}$ ($l_1^{(m)}$), and the number of White (minority) workers performing Task 2 as $l_2^{(w)}$ ($l_2^{(m)}$). So $L_1 = l_1^{(w)} + l_1^{(m)}$ and $L_2 = l_2^{(w)} + l_2^{(m)}$

We use ω_i to denote the market wages for workers performing Task i ($i = 1, 2$). The firm needs to invest in training workers before they can perform each task, so the effective labor cost is the sum of wages and training cost (c). For White workers in Task i, the effective cost is is $C_i^{(w)} = \omega_i^{(w)} l_i^{(w)} + c(l_i^{(w)})$, and the effective labor cost for hiring a minority worker in Task i is $C_i^{(m)} = \omega_i^{(m)} l_i^{(m)} + c(l_i^{(m)})$. Here, c represents the training cost, an increasing function of the number of workers: $c(l) = al + c$, where $a > 0$ because well-trained, ready-to-use workers are scarce. Higher values of a indicate greater scarcity of suitable workers. And $c > 0$ represents the minimum training cost for any worker to fit the job. These assumptions have two microfoundations. First, many high-skill jobs require firm-specific human capital and knowledge. It takes time for a new worker to build up human capital and perform tasks as proficiently as a worker with experience with the firm. Second, firms often face a limited supply of skilled workers and labor markets for talent tend to be highly competitive (He, 2018; Chen et al., 2023).

We make two important assumptions regarding the training cost for the skilled task (Task 1). First, the firm is "biased" in favor of White workers and consider them to require lower training costs to perform the skilled task. We use c_w and c_m to denote the (perceived) minimum training costs for White and minority workers, respectively. Our assumption means $0 < c_w < c_m$, which can be justified by both taste-based discrimination and statistical discrimination (Coate and Loury, 1993; Hurst et al., 2024), or by minority workers facing greater frictions prior to entering the labor market (e.g., unequal education opportunities) and inside the firm (e.g., unequal training opportunities, mentorship, and career network).

Second, we assume that skilled White workers have a steeper supply function than skilled minority workers. This could happen if White workers are better utilized in the labor market due to existing biases or frictions, and thus are less available. We use a_w and a_m to denote the slope of training costs to the quantity of White and minority workers used for Task 1. This assumption means that $a_w > a_m$.

There is no difference between White and minority workers performing the unskilled task (Task 2). Thus for simplicity, we use a_2 and c_2 to denote the slope and intercept of the training cost function for both racial groups performing Task 2.

The firm solves for the optimal labor decisions $\{l_1^{(w)}, l_1^{(m)}, l_2^{(w)}, l_2^{(m)}\}$, and borrowing decision D by maximizing the following production function:

$$max_{\{l_1^{(w)}, l_1^{(m)}, l_2^{(w)}, l_2^{(m)}, D\}} (\alpha(l_1^{(w)} + l_1^{(m)})^\rho + \beta(l_2^{(w)} + l_2^{(m)})^\rho)^{1/\rho} - RD \tag{1}$$

$$s.t. \;\; C_1^{(w)} + C_1^{(m)} + C_2^{(w)} + C_2^{(m)} \leq N + D....(\lambda) \tag{2}$$

Given the setup above, we have the following lemma:

Lemma 1 *There exists a threshold $l_1^* = \frac{c_m - c_w}{2a_w}$, such that when the firm needs more skilled workers over this threshold, it starts utilizing minority workers.*

Let $\Delta c = c_m - c_w$, then $l_1^* = \frac{\Delta c}{2a_w}$. l_1^* is the amount of White workers for which the marginal cost of using one additional White worker equals the marginal cost of using non-zero amount of minority worker. Below this threshold, the firm perceives a higher marginal cost of using any minority worker than using a White worker, so it does not allocate minority workers to Task 1. Above this threshold, the firm utilizes both White and minority workers for Task 1. Both are marginal workers and have equal marginal cost. The amount of White and minority workers performing Task 1 satisfy:

$$2a_w l_1^{(w)} + c_w = 2a_m l_1^{(m)} + c_b$$

or

$$l_1^{(w)} = \frac{a_m}{a_w} l_1^{(m)} + \Delta c \tag{3}$$

Importantly, in this scenario ($L_1 > l_1^*$), the firm increases the usage of minority workers more than White workers to satisfy an expansion of skill labor demand, because skilled

White workers has a steeper supply curve (i.e., $\frac{a_m}{a_w} < 1$).

Below, we analyze how changes in the cost of external financing (R) affect wage gap when the equilibrium Task 1 workers exceed l^*. We first make a parameter restriction:

Assumption 1 $R(\omega_2 + c_2) \geq max\{\beta^{\frac{1}{\rho}}, \beta^2\}$.

This condition means that low-skill labor is not "too cheap," so that the equilibrium is not a corner solution where firms only employ low-skill workers.

It is easy to show that when the cost of financing R decreases, the firm increases the demand for both skilled and unskilled workers. Under Assumption 1, the demand for skilled human capital increases more than unskilled human capital.

The racial pay gap is the difference between the average pay for White workers and the average pay for minority workers, $\bar{\omega}_w - \bar{\omega}_m$, where the average wage for White workers is $\bar{\omega}_w = \frac{l_1^{(w)}\omega_1 + l_2^{(w)}\omega_2}{l_1^{(w)} + l_2^{(w)}}$, and for minority workers is $\bar{\omega}_m = \frac{l_1^{(m)}\omega_1 + l_2^{(m)}\omega_2}{l_1^{(m)} + l_2^{(m)}}$. We have the following result:

Proposition 1 *Within-firm racial pay gap $\bar{\omega}_w - \bar{\omega}_m$ is an increasing function of the cost of financing, R.*

Put differently, when it is easier to raise capital, within-firm racial pay gap decreases. The key mechanism is that, as R declines, the firm invests more in the skilled task and requires more skilled workers. As its skilled labor demand exceeds l^*, the firm increasingly allocates minority workers to the skilled task. This pushes up the average compensation for minority workers relative to White workers and narrows the wage gap.

3 Background, Data, and Descriptive Evidence

3.1 Background: Anti-Recharacterization Laws

The U.S. bankruptcy codes impose an automatic stay on collateralized assets belonging to firms that file for bankruptcy. The automatic stay can significantly delay creditors' seizure of collateral till the resolution of the bankruptcy. In the process, collateralized assets may lose value, leading to creditor losses. In anticipation of these legal frictions, firms can structure special purpose vehicles (SPVs) and conduct off-balance sheet financing. Specifically, the sponsor firm sells assets to the SPVs, which in turn issue loans backed by those assets. Proceeds from the loans are transferred to the sponsor firm in exchange for the asset sale. The SPVs are generally bankruptcy remote, which means that if the sponsor firm files for bankruptcy, creditors of the SPVs can directly seize collateral assets without going through the automatic stay. This way, SPV financing protects creditors' rights by isolating them from bankruptcy costs (Gorton and Souleles, 2007). Having the option to finance through an SPV thus reduces the cost of debt financing for firms.

However, judges could recharacterize the asset transfer from the sponsor firm to the SPV as a loan instead of a true sale. This means that the collateralized assets are again under the debtor's ownership and subject to the automatic stay. In other words, recharacterization revokes the benefits of SPV financing.

Since the early 1990s, due to lobbying efforts from the financial industry (Kettering, 2010), seven states in the U.S. have passed anti-recharacterization laws (ARLs) that prevent judges from recharacterizing the asset sales between sponsor firms to their SPVs as loans. These states include Louisiana and Texas in 1997, Alabama in 2001, Delaware in 2002, South Dakota in 2003, Virginia in 2004, and Nevada in 2005. The ARLs reinstate creditor rights protection and increase the option value of SPV financing for firms incorporated in those states. Consequently, the laws allow firms to tap into different debt markets and expand their debt capacity. Recent academic evidence suggests that firms affected by the ARLs increase borrowing, adopt new technology, and innovate more (Li et al. 2016; Mann 2018; Ersahin 2020).

In 2003, the federal court overruled in favor of recharacterization in the case of *Reaves Brokerage Company, v. Sunbelt Fruit & Vegetable Company.* This ruling suggests that the federal court could overrule state-level statutes, leading to uncertain prospects regarding the effectiveness of anti-recharacterization laws at the state level (Janger, 2003; Kettering, 2010). We consider as our treatment the three ARLs passed prior to 2003, including Louisiana in 1997, Texas in 1997, and Alabama in 2001. This design choice follows

Ersahin (2020), who documents that the adoption of ARLs leads to increased skilled labor demand, an important condition for our study. Firms incorporated in these three states are classified as affected by anti-recharacterization laws. Firms incorporated outside of all seven adoption states form the initial control group.

We verify the argument that the anti-recharacterization laws facilitate firms' access to debt markets and lead firms to increase labor demand. Panel A of Appendix Table D.1 shows that after a state adopts the anti-recharacterization law, firms incorporated in that state experience a significant increase in leverage by about 3.8 percentage points, similar to estimates obtained in Li et al. (2016). This magnitude means that the average firm during our sample carries \$403 million more debt per year ($= 0.038 \times 10598$ million, where \$10,598 million is the average total assets of U.S. public firms). We further examine whether the ARLs led firms to expand their workforce using plant-level employment data from the Longitudinal Business Dynamics (LBD) maintained by the U.S. Census Bureau. Consistent with this prediction, Panel B shows that the establishments of affected firms experience around 6% employment growth following the adoption of ARLs.

3.2 Data Sources

We compile our sample from the Longitudinal Employment-Household Dynamics (LEHD) database, the Longitudinal Business Database (LBD), Revelio Labs, and Compustat. Key data cleaning and sampling steps are summarized in this section, with additional details in the Internet Appendix II.

3.2.1 LEHD, LBD and Compustat

We use the employer-employee matched data from the U.S. Census Bureau's LEHD program to determine workers' races, sex, education levels, and track workers' quarterly earnings (adjusted for inflation to 2018 constant dollars), locations, and industries across employers.[7] We limit our sample to workers between 18 and 64 years old. Each worker is

[7] We have access to LEHD for 25 participating U.S. states listed in the Internet Appendix Table IA.1 from 1990 to 2014 (except for Maryland, which starts in 1985). See more details about LEHD in the Internet Appendix and Vilhuber et al. (2018).

categorized into one of the following six racial groups: White, Black or African American, American Indian or Alaska Native, Asian, Native Hawaiian or Other Pacific Islander, or multi-race group. We define all non-White workers as minority workers.[8] To reduce computational demands, we average quarterly earnings per worker-firm pair within a year, defining our variable of interest *Log(Earnings)* as the natural log of these annualized average earnings.

To identify the state of incorporation for workers' employers, we first link worker-year data constructed from LEHD with firm identifiers in the Census Bureau's LBD through the Business Register Bridge (BRB). We then link the LEHD-LBD matched sample with Compustat using the Compustat-SSEL Bridge (CSB) to obtain employers' gvkeys and their financial data. For each gvkey-year, we merge in their historical incorporation states obtained from the SEC Analytics Suite by WRDS. We define several other firm characteristics using LBD data: firm age as the current year minus the first observed year of its oldest establishment, firm size as total employment across all establishments, and firm industry as the 4-digit NAICS industry in which they paid the highest payroll.

3.2.2 Revelio Resume Data

We obtain proprietary resume data from Revelio Labs, which covers unique identifiers of employer and employee, job titles, O*NET occupation codes, and estimated salaries. More details about Revelio data are described in the Internet Appendix II. Revelio predicts the probabilities of a worker belonging to each racial group, White, Black, Asian, and Pacific Islander, Hispanic, Native, or multiple races. We define a worker as a minority if her probability of being a non-White worker exceeds 50%. We also use the information on sex and education provided by Revelio.

We exclude non-U.S. and part-time jobs, create a worker-year panel, and match

[8] LEHD reports race and ethnicity (i.e., Non-Hispanic and Hispanic or Latino) as two separate items. Hispanic may be of any race. In addition, the ethnicity question in the Census survey was one of the most unanswered questions in surveys conducted before 2003 because it was asked after the race question and people thought they have answered the ethnicity question by answering the race question. This issue remained until the Revisions to the Standards for the Classification of Federal Data on Race and Ethnicity in 1997. For these reasons, in our baseline sample created using Census data, we do not differentiate Hispanics from other races, and define minority solely based on race.

employers to Compustat using a bridge built by Revelio Labs to collect firm incorporation states and financial information. We create several variables indicating workers' career changes. First, we identify within-firm job mobility using *New Position*, a binary variable that equals one if a worker is assigned to a different job position in the next year, and zero otherwise. Second, we define *Promotion* as an indicator for whether a worker changes to a position in the following year that offers a higher salary. Third, we define *Promotion Within Occ* as one if a worker changes to a higher-paying position within the same firm and the same three-digit SOC in the next year, and zero otherwise. Finally, we code *Change to Tech-oriented* as an indicator for whether a worker changes his/her job code from a non-tech-oriented category to a tech-oriented category within a firm.[9] All indicators are multiplied by 100, so our coefficients indicate job transition and promotion rates in percentage points.

3.3 Sample Construction

We consider a firm to be affected by the ARL if its state of incorporation is Louisiana, Texas, or Alabama, which enacted the anti-recharacterization laws prior to 2003.[10] To create a clear separation of firms affected and unaffected by the laws, we only retain firms incorporated in LA (1997), TX (1997), and AL (2001) (i.e., "affected" firms) as well as firms in never-adoption states. We further exclude financial firms, regulated utilities, and public administration.

Within our employer-employee matched samples from Census LEHD-LBD and Revelio, we classify workers to be "treated" if they were employed by an affected firm during the year preceding the passage of the laws. As prior research documents that firm characteristics are important determinants of income inequality (e.g., Song et al. 2019, Mueller et al. 2017), we carefully select a set of control workers employed by firms with similar characteristics but incorporated in never-adoption states. Specifically, we require treated and control workers to be employed by firms within the same 2-digit NAICS sector

[9]We follow Hecker (2005) and Ma, Ouimet, and Simintzi (2016) to identify tech-oriented occupations. Detailed occupational codes can be found in the Internet Appendix II.

[10]Following Li et al. (2016), we only consider the three early-adoption states because the 2003 federal court ruling introduced uncertainty to the implementation of ARLs adopted in Delaware, South Dakota, Virginia, and Nevada in later years.

and the same pre-event employment size quintile as defined in the sample.[11] To account for changes in earnings due to job transitions, we focus on workers with at least one year of work record both before and after the event and obtain their entire employment histories at an affected or control firm.

Lastly, we create a stacked panel by stacking treated workers and their matched control workers together to address concerns related to the generalized difference-in-difference regressions highlighted in contemporary work (Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021). Our Census LEHD-LBD sample includes the employment and earnings records of 453,600 unique workers at 498 unique firms.[12] The Revelio resume sample includes 3.26 million job spans of 2.67 million unique workers.[13] Both samples start from 1990, which gives us sufficient time series before the first adoption of the anti-recharacterization laws in 1997, and end in 2012 because the matching quality between LEHD and LBD worsens in 2013 and 2014.

3.4 Summary Statistics

Table 1 presents the summary statistics of the key variables used in our study. Within our Census LEHD-LBD sample, the average worker earns $14,670 per quarter, which translates to annual earnings of $58,680 in 2018 dollars. On average, workers are 40 years old and have 6 years of experience working in a firm. Around 56.6% of workers are male and 15% of workers are minorities, consisting of 4.4% Asian, 8.2% Black or African-American, and 2.1% other races.[14]

<u>TABLE 1 ABOUT HERE</u>

[11] We only have access to LEHD data from 25 states presented in Internet Appendix Table IA.1, which do not include Louisiana, Texas, and Alabama. In other words, our sample includes employees physically *located* in these 25 states whose employers are *incorporated* in either the three states that adopted the law or in states that never enacted it. By excluding workers in three adoption states, we mitigate the concern of confounding factors driving both the enactment of the ARLs and the reduction of the racial pay gap.

[12] All observation counts and estimates are rounded according to Census disclosure policies.

[13] Revelio data includes workers nationwide, while our Census project covers only 25 participating states, explaining the sample size difference between the two datasets.

[14] These numbers are comparable to the data published by the Bureau of Labor Statistics. For example, in 2022, among full-time employed individuals aged 16 years or above, 6.9% are Asian, 6.4% are Black or African-American and 56.6% are male. See more details at https://www.bls.gov/cps/cpsaat08.htm.

The average worker in our Revelio resume sample has a 3.5% likelihood of switching to a new job position within the firm. They also face about the same likelihood of being promoted to a higher-pay position, and about 1.5% of being promoted to a position in the same three-digit SOC category. Finally, we note that the likelihood of transitioning to a high-tech position is generally low, around 0.2%. The average worker also has 6 years of experience working in a firm. Around 17% of workers are non-White minorities and 64% of workers are male.

3.5 Descriptive Evidence on Racial Gaps within Firms

We begin our analysis by examining the differences in pay and career outcomes between White and minority workers in our samples. Figure 1 presents the time-series differences in average quarterly earnings between minority and White workers in our LEHD-LBD sample. Consistent with the literature, minority workers persistently earn less than their White peers, with the racial earnings gaps rising from 10.4% to 16.5% over 1990–2012.

Next, we regress several worker outcomes, including *Log(Earnings*, *New Position*, *Promotion*, and *Change to Tech Oriented*, on *Minority*, the indicator for non-White workers. Table 2 presents results from two specifications. The first includes event-by-firm and event-by-year fixed effects to track workers within firms and account for macro trends, alongside controls for firm-specific time-varying characteristics. The second adds worker-level controls (e.g., tenure, sex, education) and event-state-year and event-firm-year fixed effects to account for local conditions and firm dynamics.

In columns (1) and (2), we find that minority workers make 10–12% lower earnings compared to their White peers in the same firm with the same education, sex, and tenure. Figure 2 shows comparable pay gaps among Asians, Blacks, and other minorities compared to White peers in the same firm, with the widest pay gap between Black and White workers.

TABLE 2 AND FIGURE 2 ABOUT HERE

Results in columns (3) through (10) of Table 2 reveal that minority workers have slower career progressions compared to White peers in the same firm. Minority workers are 0.5 percentage points less likely to change job positions, 0.34 percentage points less likely to be promoted to a higher-pay position, and 0.17 percentage points less likely to advance within the same three-digit job category compared to White workers. Minority workers also have a 2-basis-point lower likelihood to switch to a technology-oriented position, which represents a 10.6% (= 0.019/0.18) difference relative to the sample mean reported in Table 1.

Figure 3 presents the shares of minority workers across different seniority levels inside firms in our Revelio resume sample.[15] Minority workers account for 19% of total entry-level workers, but only 13% of vice presidents or directors, and less than 11% of C-suite jobs. These patterns suggest that minority workers potentially face frictions preventing them from moving up the job ladder, and the lack of vertical movement could contribute to the racial pay gap inside firms.

FIGURE 3 ABOUT HERE

4 Empirical Framework

We employ a triple-difference-in-difference framework to examine the differential effect of anti-recharacterization laws on White and minority workers. Specifically, we estimate the differential treatment effect on minority workers' earnings (i.e., β) relative to White workers in the following regression using the Census LEHD-LBD sample:

$$Log(Earnings)_{i,e,f,t} = \beta Treat_f \times Post_{e,t} \times Minority_i + \theta Treat_f \times Post_{e,t} + \gamma Minority_i \times Post_{e,t} + \alpha_{e,i,f} + \mu_{e,f,t} + X_{e,i,f,t} + \epsilon_{i,e,f,t}, \quad (4)$$

where i is an individual, f represents a firm, and t is a year. e indicates an ARL event, which includes all observations related to a matched group of treated and control firm

[15]Revelio creates a seniority index using an ensemble model, based on information regarding the title, company, industry, and an individual's job history and age. See more details at https://www.data-dictionary.reveliolabs.com/methodology.html#seniority. This index, while well suited for comparing worker seniority within each firm, can be a coarse metric of workers' career progression. We thus rely on salary information to infer promotions.

observations. $Treated_f$ equals one if firm f is incorporated in any of the three states that passed an anti-recharacterization law prior to 2003. $Post_{e,t}$ turns to one for years after the inception of the laws under event e. $Minority_i$ equals one for nonwhite workers.[16]

Similar to before, we control for a rigorous set of controls ($X_{e,i,f,t}$) to remove potential confounding effects, including event-state-year, event-industry-year, event-sex-year, and event-education-year fixed effects, as well as firm characteristics and worker tenure. Moreover, we include event-worker-firm fixed effects ($\alpha_{e,i,f}$), which allow us to track a worker's earnings inside a firm over time, and eliminate effects related to worker-firm matching around a specific event. We also control for event-minority-year fixed effects, which absorb the coefficient from *Minority*×*Post* and account for the differential evolution of the earnings gap among worker types across matched groups. In the strictest specifications, we impose event-firm-by-year fixed effects ($\mu_{e,f,t}$), which control for firm-specific trends and narrow down the comparison to only White and minority workers within the same firm. Standard errors are clustered by the state where individual i works.

Using the resume data, we estimate the differential treatment effect on minority workers' promotion probability using a similar regression framework:

$$Y_{i,e,f,t} = \beta Treat_f \times Post_{e,t} \times Minority_i + \theta Treat_f \times Post_{e,t} + \gamma Minority_i \times Post_{e,t} + \eta Treat_f \times Minority_i + \alpha_{e,f} + \tau_{e,t} + X_{e,i,t} + \epsilon_{i,e,f,t}, \quad (5)$$

where Y includes *New Position*, *Promotion*, *Promotion Within Occ*, and *Change to Tech-oriented*. Our estimation includes event-firm ($\alpha_{e,f}$) and event-year($\tau_{e,t}$) fixed effects. In this analysis, since individual workers face few promotions, we follow Benson et al. (2024) and do not include worker fixed effects in the regression. But, in some specifications, we additionally control for a set of worker characteristics ($X_{e,i,t}$), including worker tenure, event-education-year fixed effects, event-sex-year fixed effects, event-minority-year fixed

[16] LEHD reports race and ethnicity (i.e., Non-Hispanic and Hispanic or Latino) as two separate items. Hispanic may be of any race. In addition, the ethnicity question in the Census survey was one of the most unanswered questions in surveys conducted before 2003 because it was asked after the race question and people thought they have answered the ethnicity question by answering the race question. This issue remained until the Revisions to the Standards for the Classification of Federal Data on Race and Ethnicity in 1997. For these reasons, in our baseline sample created using Census data, we do not differentiate Hispanics from other races, and define $Minority_i$ solely based on race. In untabulated results, we observe consistent outcomes when including White Hispanics within the minority group.

effects, event-state-year, as well as event-occupation-year fixed effects. Standard errors are clustered by worker state. Again, we are interested in β, which captures the differential effects of ARLs on promotion rates and job mobility for minority workers relative to White workers.

5 Main Findings

5.1 Baseline Results

Table 3 presents the main findings of our study. We estimate Equation (4) using the matched event-worker-year panel from the Census LEHD-LBD data. We report six specifications with progressively rigorous fixed-effect structures. Across all specifications, *Treated*×*Post*×*Minority* generates a positive and statistically significant coefficient, suggesting that after the adoption of the anti-recharacterization laws, minority workers experience a higher increase in earnings than White workers in affected firms. The most stringent specification (column (5)) suggests that in treated firms, minority workers observe around a 3% greater increase in earnings compared to White workers in the same firm and time, with the same sex and education levels.

TABLE 3 ABOUT HERE

While a 3-percentage-point reduction in the racial pay gap is substantial compared to the overall racial earnings gap in our sample firms of around 10% (see Table 2), it does not represent an overly large amount of spending. In our sample, the average firm employs 3,619 workers, 14.8% of whom are minority workers (around 536 workers), and the average minority worker makes $12,720 per quarter. A 3-percentage-point raise to minority workers translates into about $0.86 million per quarter increase in payroll ($= 0.03 \times 536 \times \$12720 \times 4$). This amount is relatively small compared to additional debt raised post ARLs (around $403 million, see Section 3.1).

The higher wage growth among minority workers is also consistent with the fact that minority workers tend to have higher labor supply elasticity than White workers, meaning that it is more cost-effective to induce an increase in labor supply from minority workers than from White workers. According to Bartik (2008), labor supply elasticity is estimated to be 0.64 for Black workers and 0.18 for White workers. Consider a firm seeking to expand its work force by 2%, whose labor composition fits the average profile in our sample (Table 1): 14% of workers are minority and 86% are White . If the expansion were to purely come from White workers, this would only lead to a 2.3% (= 0.02/0.86) White worker growth, which can be induced by a 13% wage increase for White workers(= 0.023/0.18). If instead, the expansion were to purely come from minority workers, this leads to a 14.3% minority employment growth (= 0.02/0.14), which can be induced by a 22% wage growth for minority workers (= 0.143/0.64). These two extreme cases suggest that the expansion can narrow or widen the racial pay gap, ranging from -22% to 14.3%, depending on how the growth is allocated. In a "balanced" scenario where 1% of growth comes from each racial group, minority workers will face an 11% increase in pay while White workers face a 6.5% increase, which narrows the pay gap by 4.5%.

What race drives this effect? We next decompose *Minority* into three groups, including *Black*, *Asian*, and *Other* and re-estimate Equation (4). Table 4 reports the results from the same set of specifications as in our baseline analysis (Table 3). We find that both Black and Asian workers experience substantially higher earnings increases than White workers after the laws. Specifically, the triple interaction coefficient is 3%–6% for Asian and Black workers, with Black workers experiencing the strongest increase. There is little effect arising from other minority groups, which include American Indian or Alaska Native, Native Hawaiian or Other Pacific Islander, or multi-race group.

TABLE 4 ABOUT HERE

5.2 Dynamic Effects

We examine how access to debt markets dynamically influences the racial earnings gap by investigating the evolution of worker earnings every year within the event window. This investigation allows us to verify the parallel trend assumption for difference-in-difference settings.

We estimate the dynamic effects of ARLs within a window spanning two years prior to the event and over three or more years afterward. The length of the window is designed to resemble the average job tenure of 6 years. Our estimation proceeds in two steps. First, we estimate coefficients from the triple difference design as follows:

$$Log(Earnings)_{i,e,f,t} = \sum_{k=-2}^{3+} \phi_k 1_{t=e_t+k} \times Treated_f \times Minority_i + \alpha_{e,i,f} + \mu_{e,j,t}$$

$$\mu_{e,s,t} + X_{e,i,f,t} + \epsilon_{i,e,f,t}, \quad (6)$$

where k represents each year during the adoption of the laws. e_t is the year of the adoption. $1_{t=e_t+k}$ is an indicator that equals one if the current year is k years after the year of the event. $\alpha_{e,i,f}$ represents worker-by-firm fixed effects. $\mu_{e,j,t}$ represents event-industry-year fixed effects. $\mu_{e,s,t}$ represents event-state-year fixed effects. Other controls ($X_{e,i,f,t}$) are the same as the ones described in Equation (4). $Treated_f \times Minority_i$ is absorbed by worker-by-firm fixed effects. The interactions of $Minority_i$ and event time dummies are absorbed by event-minority-year fixed effects. We are interested in ϕ_k, which capture time-varying effects of financing shocks on racial pay gaps over the event horizon.

Second, we separately examine how earnings evolve for minority and White workers around the passage of ARLs. This helps ease the interpretation of the triple-interaction coefficients and validates that the reduction in the earnings gap is not driven by a reduction in White workers' earnings. We thus estimate the following regression for each of the subsamples:

$$Log(Earnings)_{i,e,f,t} = \sum_{k=-2}^{3+} \phi_k 1_{t=e_t+k} \times Treated_f + \alpha_{e,i,f} + \mu_{e,j,t} + \mu_{e,s,t} + X_{e,i,f,t} + \epsilon_{i,e,f,t}, \quad (7)$$

Given that this model is estimated on subsamples of minority and White workers separately, we no longer include the triple interaction of *Minority*, *Treat*, and event time indicators. Controls are the same as the ones described in Equation (6), except that event-minority-year fixed effects are excluded from Equation (7). For each group of workers, we are interested in ϕ_k, which indicates the timing and the extent of the effect of firm financing shocks on worker pay.

Figure 9 reports the results from this analysis. Year 0 (i.e., the year of the law adoption) is absorbed as the benchmark year, so all coefficients reflect the changes in worker earnings relative to their Year-0 levels. Panel A reports the coefficients from the triple difference designs, based on Equation (6). Panels B and C report estimates for minority and White workers, respectively, based on Equation (7). From both specifications, we do not observe any significant changes in the earnings of minority or White workers prior to the passage of the ARLs. Panel B shows that, after the passage of the laws, earnings of both minority and White workers increase. However, the earnings growth for minority workers is larger than that of minority workers. As a result, the pay gap between White and non-White workers is significantly reduced after 2 years, as shown in Panel A.

Overall, findings from this analysis confirm that workers' earnings do not change prior to the law adoption, but increase significantly after the events. They also show that the narrowing of the racial earnings gap is driven by the greater increase in earnings for minority workers but not by the decline in White worker earnings.

6 Mechanisms

In this section, we explore potential mechanisms underlying our main findings. One possible explanation is that the ARL laws may have increased the returns to low-paying or low-skill positions, increasing the income of minority workers who are disproportionately represented in these positions. According to this explanation, low-skill, low-income minority workers should be most affected by the shocks.

Another possible explanation is a "human capital utilization" channel. Due to biases or labor frictions inside firms, minority workers are ex-ante matched to lower-paying positions, or worse-fit tasks for their skills, compared to White workers. The laws relax firms' financing frictions, leading to greater skilled labor demand. To the extent that White workers are relatively well-matched to their current positions, firms are more likely to open up job opportunities to minority workers inside the firm. Consequently, minority workers are matched to higher-paid or better-fit positions.

In contrast to the previous explanation, the human capital utilization channel does not predict a stronger effect for low-skill minority workers. Instead, results should be stronger for skilled workers, who possess task-specific or firm-specific human capital that makes them difficult to replace with candidates outside the firm. We should also observe more frequent job switches by minority workers, especially to higher-paid, higher-skilled positions inside firms.

We further investigate the relevance of other labor market frictions. For example, the existence of racial inequality suggests that minority workers face certain biases inside the firm or labor market frictions that prevent them from moving up the job ladder. To the extent that financing-induced demand may overcome those frictions, we conjecture that our effects should be stronger in cultural environments that tolerate greater inequality.

Finally, we expect our effects to be stronger in tighter labor markets and where White workers are in relatively short supply. In those areas, firms with growing labor demand have to allocate more jobs to minority workers.

6.1 Differential Effects Across Worker Skill

We examine whether financial shocks affect higher-skill or lower-skill workers differently. While worker skills are not directly observable, we rely on two proxies. First, we examine worker education provided by the LEHD program and define four categories of educational attainment: below high school, high school, some college, and college and above. Second, we use workers' prior income as a proxy for skill. This measure is motivated by the persistent skill premium in the U.S., where a significant portion of the variation in worker pay is linked to labor skills (Juhn et al., 1993; Acemoglu and Autor, 2011; Guvenen et al., 2014). We sort workers into low-, middle-, and high-skill groups using their averaged quarterly earnings during the year prior to the adoption of the anti-recharacterization laws.

We examine the differential earnings growth between minority and White workers at different skill levels using a quadruple difference-in-difference framework. Formally, we estimate the following model:

$$Log(Earnings)_{i,e,f,t} = \sum_s \beta_s Treated_f \times Post_{e,t} \times Minority_i \times 1^s_{e,i,t}$$
$$+ \sum_s \gamma_s Treated_f \times Post_{e,t} \times 1^s_{e,i,t} + \alpha_{e,i,f} + \mu_{e,f,t} + X_{e,i,f,t} + \epsilon_{i,e,f,t}, \quad (8)$$

where 1^s indicates worker i's skill type s, and β_s reveals the effect of the financing shock on the racial earnings gap within skill s. We follow the specification in column (5) of Table 3, including controls for worker tenure, event-firm-worker fixed effects, as well as interactions of event-year fixed effects with other worker characteristics and firm fixed effects.

Figure 9 plots the coefficient estimates for $\{\beta_s\}$. Panel A provides results related to worker skill defined by education, while Panel B reports results where worker skill is defined by their pre-event earnings. Across both measures of labor skill, we find that better access to debt markets does not reduce the racial pay gap among low-skill workers, but substantially narrows the pay gap for medium- and high-skill workers. The estimates suggest that the racial pay gap between minority and White workers reduces by about 4%, on average, following the passage of ARLs for workers with a high-school or college degree, and for workers with medium or high pre-event income.

These results are at odds with the argument that the increases in minority workers' earnings are driven by a higher return to low-paying/skill, minority-dominated positions. Instead, they are consistent with the human capital utilization channel, i.e., minority workers have access to more job opportunities and better-fit tasks (positions) as their employers have easier access to external debt markets.

6.2 Effects on Worker Careers

We next use the resume sample described in Section 3 to further validate the human capital utilization channel. In Table 5, we investigate whether better access to financing affects the career development of minority and White workers differently. Each panel presents results for a career outcome variable, including indicators for having a new position, promotion, promotion within the same occupation, and reallocation to tech-oriented positions. We layer on controls and fixed effects in stages. In Panel A, we find that minority workers are more likely to obtain a new position following the adoption of anti-recharacterization laws compared to White workers. The coefficient from the most stringent specification (column (7)) suggests that the job mobility gap between minority and White workers reduces by 0.2 percentage points, about 40% of the averaged gap reported in Panel B of Table 2 (= 0.196/0.486). In Panel B, as compared to White workers, we find that minority workers are more likely to be promoted, defined as a worker moving to a new position with a higher salary. This effect also generates sizable economic magnitudes, around 57% of the sample mean (= 0.195/0.34). Panel C further shows that minority workers are more likely to face promotion within the same three-digit occupation code. Finally, in Panel D, we find that minority workers experience a greater increase in the likelihood of switching to a technology-heavy occupation compared to White workers after the adoption of ARLs.

Table 5 About Here

These results are in line with the previous evidence suggesting that the financing shocks mostly influenced skilled minority workers. Consistently, we observe minority workers to be more likely to switch technology-oriented occupations and be promoted to more senior, higher-pay positions. These findings further support the human capital utilization channel, i.e., better access to financing improves the utilization and development of minority workers' human capital.

6.3 The Role of Pre-Existing Inequality

The human capital utilization channel suggests that biases or frictions inside the firms prevent them from fully utilizing the human capital of minority workers. We gauge the relevance of such frictions by examining whether pre-existing racial inequality or norms inside the firm can moderate our effects. We design two analyses along this line. First, we compute the racial pay gap inside firms during the year prior to the financing shock, which sheds light on the pre-existing inequality inside firms. Second, we measure the demographic diversity among the board of directors following Bernile et al. (2018) and Genin et al. (2023). Specifically, board diversity is a linear combination of the standardized values of (1) the share of female directors, (2) the standard deviation of director ages, and (3) negative Herfindahl–Hirschman index (HHI) in director ethnicity.[17] Cai et al. (2022) find that greater board diversity is associated with more diverse workforce hiring and more inclusive corporate cultures.

Similar to the way we categorize worker skill levels, we create tercile indicators for pre-event pay gap and board diversity, and interact each of the tercile indicators with *Treated*×*Post*×*Minority*, and estimate Equation (8). Figure 9 shows the results. The reduction in the pay gap is concentrated among firms with more severe racial inequality ex ante, represented by relatively higher racial pay gaps and lower levels of board diversity. In other words, better access to debt increases minority pay in workplaces with worse ex-ante diversity practices. These patterns highlight the important role of corporate finance in alleviating the labor market frictions faced by minority workers.

6.4 Local Labor Market Tightness and White Worker Share

As firms expand and increase the demand for skilled jobs, they have the option to search for such workers from outside the firm or to allocate job opportunities to White workers. These strategies can become challenging in tight labor markets where there are few skilled workers available, or in areas with a lower proportion of White workers. In those cases, firms have to rely more on minority workers to fill their growing labor demand. We thus expect our effects to be more pronounced in tight labor markets and areas with a lower fraction of White workers.

We gauge labor market tightness using unemployment rates, where a lower unemployment rate indicates a tighter labor market. We also compute the White worker share, i.e.,

[17]HHI in directory ethnicity is constructed as the sum of the squares of director ethnicity shares within the board of a given firm-year. A higher HHI indicates a greater concentration of board members' races within a single group, so we employ a negative HHI to measure diversity.

the percentage of workers who are White . Both measures are computed at the commuting zone level for the year before the adoption of the law.[18] We create tercile indicators of each measure, interact each of them with *Treated*×*Post*×*Minority*, and estimate Equation (8).

Figure ?? provides the results from this analysis. Consistent with our conjecture, the narrowing of the earnings gap is most pronounced in commuting zones with low unemployment rates and low shares of White workers, where firms are likely to face challenges in hiring (White) workers externally. In these areas, firms seeking to increase the usage of skilled workers likely have to rely on minority workers inside the firm to a greater extent.

7 Extensive Margins and Long-Run Effects

In the analysis so far, we have focused on the earnings growth of existing workers who remain in the firm. We now shift our lens to the extensive margin and study the effect of debt capacity on the racial retention gap and the racial pay gap for new hires. We also track the long-term earnings of workers who leave their employers eventually.

7.1 Separation and New-Hire Earnings

We estimate Equation (4) to examine whether firms' access to financing influences the separation likelihood of White and minority workers, as well as the new-hire pay gap between the two groups. In this analysis, we drop individual fixed effects because separation and entry rarely repeat for the same individual and firm.

Panel A of Table 6 reports the results for separation likelihood, defined using employer-employee matched data from LEHD and LBD programs. We find that following the ARLs, the average treated worker becomes less likely to separate from their employers, but the changes in separation rates are not significantly different between White and minority workers. Thus, while increased debt financing reduces the racial pay gap, minority workers are not more likely to be retained by the firm than White workers.

[18] Commuting zone-level unemployment rates are calculated based on statistics published by the Bureau of Labor Statistics, which are publicly available at https://www.bls.gov/lau/tables.htm#cntyaa. White worker shares are calculated using LEHD data.

Table 6 About Here

We next focus on the earnings of newly hired workers. New hires are identified in employer-employee matched data from LEHD-LBD and defined as workers with a tenure of 0 or 1, indicating that they have just started working for the employer. Results in Panel B of Table 6 suggest that after the ARLs, newly hired minority workers experience around 6% higher earnings growth compared to newly hired White workers. The magnitude of this effect is more pronounced for new hires than for incumbent workers. There are at least two explanations. First, compared to new hires, incumbent workers may be willing to take a smaller raise, because exploring outside options may lead to losing their firm-specific human capital (Burdett, 1978; Black, 1981). Second, to employ minority workers for skilled positions, firms may directly search for qualified workers outside the firm or invest in incumbent workers through training. The additional training costs invested in incumbent workers could contribute to the differential pay raise observed among new hires.

7.2 Long-Run Effects

Our evidence so far suggests that minority workers benefit from better access to financing by employer. What happens when those workers leave the treated firm to join another? Does the labor market undo the earnings gain?

To answer this question, we decompose *Post* into two indicators: *Post (Same Firm)* equals one after the passage of the anti-recharacterization laws and before a worker leaves his employer at the time of the event. This indicator turns to zero when the worker departs the original employer. *Post (Different Firm)* turns to one once the worker joins another employer. This variable equals zero before the job switch. We interact both indicators with *Treated* and *Minority* in the triple-difference-in-difference framework described in Equation (4). Coefficients on *Treated* $\times$ *Post (Same Firm)* $\times$ *Minority* represent the direct effect of the laws on minority workers through the affected employers, while coefficients on *Treated* $\times$ *Post (Different Firm)* $\times$ *Minority* compares workers' income after their job switch to the pre-event levels, thus capturing the long-run effects. Since we allow workers to switch employers, we no longer control for interactive effects related to firm and industry, such as event-firm-year and event-industry-year fixed effects.

Results are shown in Table 7. This table follows the same specifications as our baseline analysis (Table 3). We find that *Treated* × *Post (Same Firm)* × *Minority* and *Treated* × *Post (Different Firm)* × *Minority* both generate a positive, statistically significant coefficient with similar magnitudes. This means that minority workers receive an increase in earnings from the original employer after the law's adoption, and this earnings gain persists even if the workers join a new employer. Across all columns, the equality tests between the coefficient estimates on *Treated* × *Post (Same Firm)* × *Minority* and *Treated* × *Post (Different Firm)* × *Minority* fail to reject the null hypothesis that earnings increases are the same across the original employer and new employer, with P-value all above 0.80. In other words, the labor market does not undo the effect of the financial shock, either because the affected workers have accumulated more human capital, or because the elevated earnings serve as a benchmark for future pay negotiations.

TABLE 7 ABOUT HERE

8 Additional Analyses

8.1 External Validity

To evaluate the external validity of our findings, we estimate the effect of firms' access to external debt markets on racial pay gap in an alternative setting, where firms face *negative* debt financing shocks. We expect racial gaps to widen in firms that face challenges in raising debt. To this end, we utilize the expiration of debt at the onset of the Global Financial Crisis (GFC) as plausibly exogenous shocks to firms' access to external credit markets (Duchin et al., 2010; Almeida et al., 2011; Carvalho, 2015). This strategy is built on the facts that the arrival of the GFC was largely unanticipated, and the cost of debt financing skyrocketed during the GFC. Thus, firms that had a large amount of debt maturing during the GFC likely faced significant challenges raising new debt and rolling over existing debt obligations. This represents an important external financing constraint.

Since the GFC started in the third quarter of 2007, we follow Duchin et al. (2010) and define "treatment intensity" using the amount of net short-term debt (i.e., short-term debt after subtracting cash and cash equivalents) on a firm's balance sheet as of July 2006 that matures in one year($\textit{Short-term Debt}_{2007}$).[19] A greater amount of net short-term debt potentially suggests that a firm needs to finance a larger amount of debt during the GFC, and thus more severe external financing constraints faced by the firm. We then regress worker earnings (or career outcomes) on the full interaction of $\textit{Short-term Debt}_{2007}$, an indicator for post-2007 years ($Post_{2007}$), and *Minority*, controlling for the same set of control variables as in column (5) of Table 3 (or Table 5). Following Duchin et al. (2010), our sample includes U.S. public firms outside the finance and utilities sectors and spans from 2006 to 2008. Table 8 reports the result.

TABLE 8 ABOUT HERE

Our results suggest that minority workers fare worse than their White peers in financially constrained firms. A one-standard-deviation increase in a firm's net short-term debt maturing in 2007 is associated with 0.3 percentage points slower earnings growth for minority workers compared to White workers. The estimated difference is statistically significant at 1%. Minority workers also exhibit worse career progressions than White workers, including lower job mobility and smaller promotion rates, although the estimates are statistically insignificant.

8.2 SPV Usage

We next validate the importance of SPVs as a mechanism through which the anti-recharacterization laws affect firms' ability to raise debt financing. Under these laws, firms have an expanded debt capacity because they can tap into various debt markets and raise off-balance sheet debt through SPVs. If our results indeed stem from firms' ability to raise

[19]We collect U.S. publicly listed firms' financial data from Compustat. $\textit{Short-term Debt}_{2007}$ = (short-term debt + long-term debt maturing in less than one year − cash and cash equivalent) / total book asset. To simplify interpretation, it is standardized to have a mean of 0 and a standard deviation of 1.

off-balance sheet financing, we expect the effects to become stronger for firms that have outstanding SPVs, who can more directly enjoy the benefit of the anti-recharacterization laws.

We follow Feng et al. (2009) and collect firms' disclosure of SPV-like subsidiaries. Specifically, we proxy for a firm's usage of SPVs using the existence of limited partnerships, limited liability partnerships, limited liability companies, and trusts among the firm's subsidiaries and affiliates that are disclosed in Exhibit 21 of the SEC Form 10-K. Accordingly, we create an indicator for *Has SPV* that equals one if a firm discloses at least one SPV-like entity in Exhibit 21 during our sample period, and zero otherwise. Analogously, *No SPV* indicates that the firm has no SPV outstanding. In Table 9, we find that the effect of the ARLs on the within-firm earnings gap is driven by firms that likely have an established SPV. This result helps validate the channel that ARLs affected worker compensation by increasing firms' ability to raise debt through SPVs.

TABLE 9 ABOUT HERE

8.3 Robustness Analyses

We carry out a battery of robustness analyses. To start, we examine the changes in relative pay rank of White and minority workers. Research on racial inequality suggests that it is important to look at both the level of earnings gap and the earnings rank gap between White and non-White workers (Bayer and Charles, 2018). To the extent that non-White workers may take different positions in the firm compared to White workers, the changes in earnings gap could be driven by workers changing their job/pay rank, or by the changes in the earnings inequality among ranks inside the firm. To investigate these possibilities, we re-estimate Equation (4) by substituting the dependent variable to be *Pay Rank*, the percentile ranking (1–100) of an individual's annual earnings relative to their peers inside the firm during the year before the event. This test helps shed light on whether the changes in the racial earnings gap are purely driven by changes in the pay between high- and low-rank employees inside the firm, or the changes in the relative job rankings for minority and White workers.

Panel A of Table 10 presents the results from this analysis. Similar to the baseline results, we add controls and fixed effects in stages. We find that better access to debt markets improves the relative pay rank of minority workers, narrowing the gap by around 2 percentiles. This estimate is stable and consistent across all columns, suggesting that our effects are unlikely to be explained by worker or firm characteristics.

Table 10 About Here

We then consider the role of the federal court ruling for *Reaves Brokerage Company, Inc v. Sunbelt Fruit & Vegetable Company, Inc. (336 F.3d 410, 413 (5th Cir. 2003))*. In this bankruptcy case, the federal court overruled the anti-recharacterization law statute in Texas and re-characterized the transfer of assets from the debtor to its SPV as a loan. While this ruling does not nullify the existing and future anti-recharacterization laws at the state level, it does introduce some uncertainty to the effectiveness of those state laws. In our baseline framework, we already take this ruling into account and exclude from our sample the state laws passed after 2003. Yet, for the early-adoption state (LA, TX, and AL), we continue to assign *Post* to be one after 2003. This is to account for the stickiness of salaries in the labor markets. In other words, minority workers who were affected by the earlier laws may continue to enjoy a raised income level even after those laws become less effective. Indeed, we confirm in Table 7 that minority workers observe a persistent earnings increase, even when they leave the treated firms.

We now gauge the direct effect of the laws passed prior to 2003 on minority workers by turning the indicator for law adoption to zero after 2003 (Li et al. 2016; Ersahin 2020). We label this new indicator as *Treat (on-off)*. The coefficient for *Treat (on-off)* × *Post* × *Minority* captures the effect of the laws before the federal court ruling in 2003. Panel B of Table 10 presents the results. The layout of this table strictly follows the baseline setup. We continue to find a significant, positive coefficient on the triple interaction term, suggesting that the earlier-adopted laws increased minority workers' earnings by around 1.6 to 3 percent more than White workers' earnings. This effect is slightly smaller than the baseline estimate, likely because we no longer account for the persistence of earnings in the long run.

In Panel C, we use an alternative method to cluster our standard errors. In our baseline analyses, standard errors are clustered by workers' state of employment to account for the fact that worker earnings are correlated within a local labor market. Now we cluster standard errors by firms' state of incorporation. Our results stay unchanged.

Worker races are imputed by the Census Bureau when missing.[20] In Panel D, we exclude workers whose races are imputed and only focus on those whose races are reported. These individuals account for 95% of our sample observations. Restricting to these individuals does not change our results.

We next discuss the possibility that our findings may be primarily driven by the earnings gap between immigrants and U.S. nationals. Results in Panel A of Table 11 suggest that both types of workers explain our effects, with similar magnitudes.

TABLE 11 ABOUT HERE

Finally, we separately gauge the effect of firm financing shocks on the earnings of female and male minority workers. Results are presented in Panel B of Table 11. Interestingly, we find that earnings growth following the ARLs is concentrated among male minority workers, with no improvement among female minority workers. These findings likely suggest that female minority workers are constrained by other labor market frictions that are not alleviated by better access to finance. For example, women may prefer flexible work hours (Goldin, 2014), which is less likely to be offered when firms expand and increase labor demand.

9 Conclusion

This paper investigates the role of access to financing in shaping the racial inequality within firms. Using employer-employee matched data administrated by the U.S. Census Bureau, we show that with better access to financing, firms substantially reduce the racial pay gap.

[20] See more details about the imputation process in Internet Appendix II.

Our empirical strategy takes advantage of the staggered passage of anti-recharacterization laws across states and compares affected and unaffected individuals working in the same labor market and industry. The granularity of the administrative data allows us to contrast minority and White workers in the same firm, with the same sex, tenure, and educational attainment. These empirical design choices help rule out multiple alternative explanations. For example, our results are unlikely to be driven by intrinsic differences across workers (aside from their race) or dynamic worker-firm matching. We also rule out the explanation that low-skill tasks (potentially disproportionately more by minority workers) are better compensated after the passage of the anti-recharacterization laws.

We find that following positive financing shocks, the increase in earnings is concentrated among middle- or high-skill minority workers. Minority workers are also more likely to switch to higher-pay, higher-skill positions inside firms. These findings indicate that firms better utilize the human capital of minority workers when they have higher debt capacity. As documented in prior literature, anti-recharacterization laws allow firms to invest in innovation and new technology. These mechanisms could lead to more career opportunities for employees, especially for minority workers whose human capital may have been under-utilized before the shocks.

This study is the first to provide causal evidence that the ability to raise debt financing narrows the racial pay gap within firms. We not only improve the identification strategy by utilizing idiosyncratic shocks to financing, but also shed light on the underlying mechanisms. Importantly, our results inform the current debate regarding corporate social responsibility, showing that firms' ability to combat racial inequality critically depends on their access to financial resources.

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Figure 1. Earnings of White and Non-White Workers Over 1990-2012
The figure plots average quarterly earnings, adjusted to 2018 Q3 dollars, for non-White and White workers in our Census sample over 1990-2012.

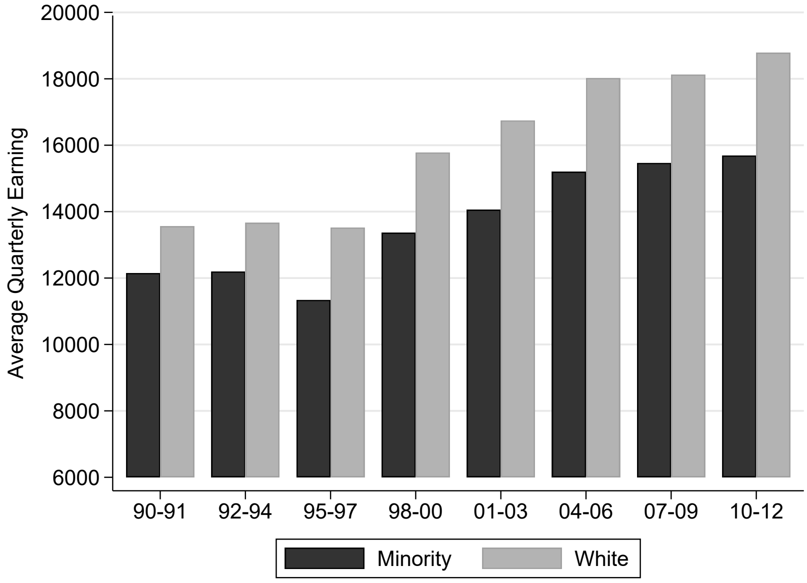


Figure 2. Racial Pay Gaps by Race
The figure plots the racial pay gaps estimated separately for Black, Asian, and other minority groups (including American Indian or Alaska Native, Native Hawaiian or Other Pacific Islander, or multi-race group), relative to White workers. The pay gaps are estimated using an OLS model with the logarithm of average quarterly earnings (*Log(Earnings)*) as the dependent variable and controls for worker characteristics (tenure, event-sex-year, and event-education-year fixed effects), event-state-year, and event-firm-year fixed effects. The underlying sample is our Census LEHD-LBD sample that spans from 1990 to 2012. Detailed variable definitions are provided in Appendix A.

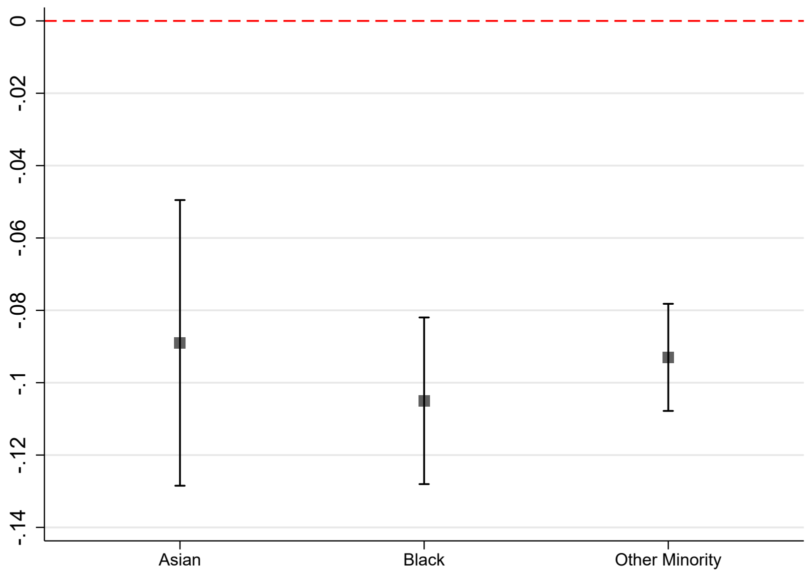


Figure 3. Minority Worker Share by Job Seniority
The figure plots the percentage of workers who are non-White at each job seniority level in our Revelio resume sample. Jobs are categorized into seven seniority levels by Revelio Labs: entry, junior, associate/analyst, manager, vice president, director, and C-suite. Examples include: 1. Entry level (e.g., Software Engineer Trainee, Paralegal); 2. Junior Level (e.g., Account Receivable Bookkeeper, Junior Software QA Engineer, Legal Adviser); 3. Associate/Analyst Level (e.g., Senior Tax Accountant; Lead Electrical Engineer; Attorney); 4. Manager Level (e.g., Account Manager; Superintendent Engineer; Lead Lawyer); 5. Vice President Level (e.g., Chief of Accountants; VP Network Engineering; Head of Legal); 6. Director Level (e.g., Managing Director, Treasury; Director of Engineering, Backend Systems; Attorney, Partner); 7. C-suite Level (Ex. CFO; COO; CEO).

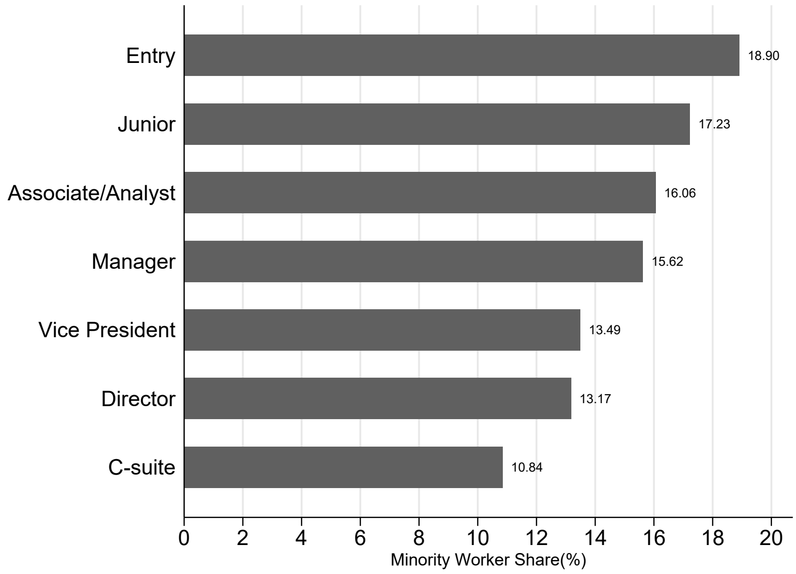
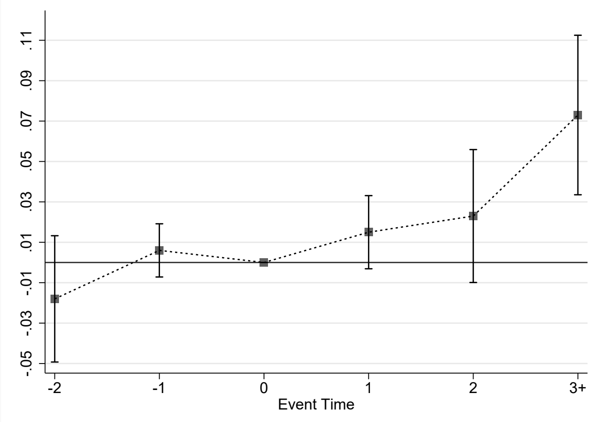
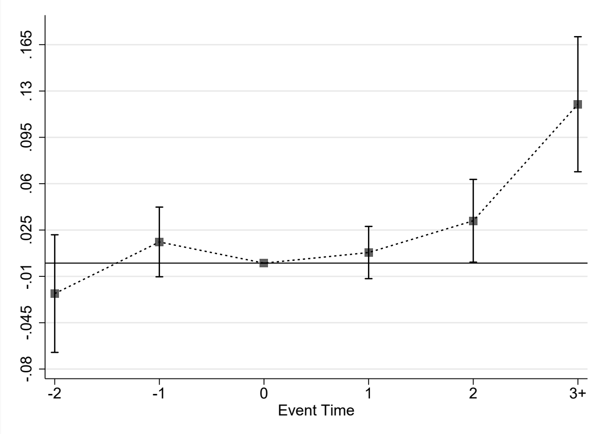


Figure 4. Dynamic Effects of ARLs on Worker Earnings

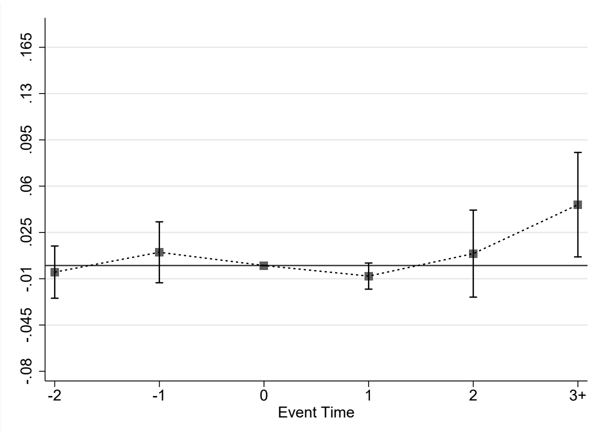
The figure plots the dynamic effects of the ARLs on the earnings gap between minority and White workers within firms, estimated using our Census LEHD-LBD sample. The dependent variable is the logarithm of average quarterly earnings in a year (*Log(Earnings)*). Panel A presents dynamic coefficients of the triple difference terms ($1_{t=e_t+k}\times$ *Treat*$\times$ *Minority* in Equation (6)), indicating effects on the earnings gap. Panel B (Panel C) reports dynamic difference-in-difference coefficients ($1_{t=e_t+k}\times$ *Treat* in Equation (7)) for minority (White) workers, indicating the changes in earnings for minority (White) workers around the event relative to the event year. The vertical lines represent the associated 90% confidence intervals. Standard errors are clustered by workers' state. Detailed variable definitions are provided in Appendix A.



Panel A: Earnings Gap (Triple Interaction Coefficients)

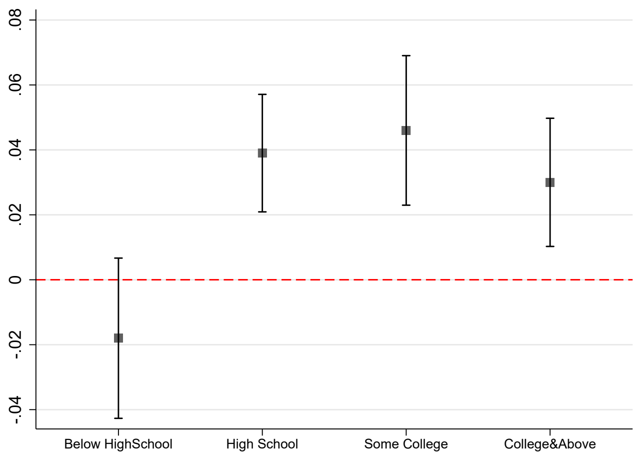


Panel B: Minority Worker Earnings

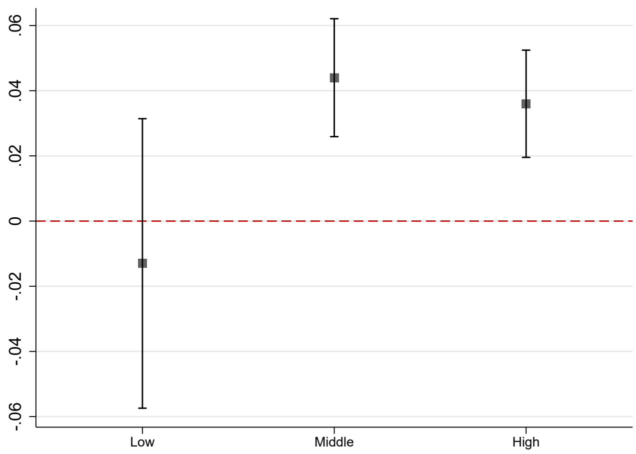


Panel C: White Worker Earnings

Figure 5. Heterogeneity of Effects by Worker Skill Levels
The figure plots the differential effects of the ARLs on the earnings gap between minority and White workers within firms by measures of worker skill levels. The dependent variable is the logarithm of workers' average quarterly earnings in a year ($log(Earnings)$). Panel A presents coefficient estimates for the interaction of $Treated \times Post \times Minority$ with indicators for different levels of worker education, categorized as below high school, high school, some college, and college and above. Panel B reports the interactive coefficients with indicators for low, middle, and high worker skill levels, measured based on terciles of average quarterly earnings in the year prior to the event. The dots in each panel indicate the point estimate of $Treated \times Post \times Minority$ interacted with each tercile indicator, indicating the differential change in earnings for minority workers relative to White workers in a skill category. The vertical lines represent the associated 90% confidence intervals. All regressions include the same controls as Column (5) of Table 3, including controls for worker tenure, event-firm-worker fixed effects, as well as interactions of year fixed effects with other worker characteristics and firm fixed effects. Standard errors are clustered by workers' state. Detailed variable definitions are provided in Appendix A.

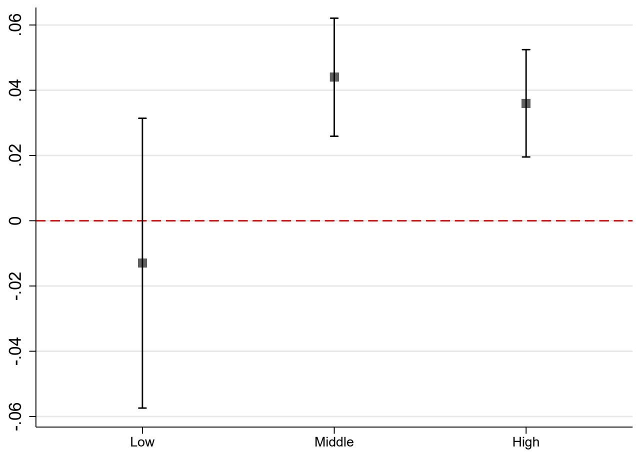


Panel A: Differential Effects Across Worker Education

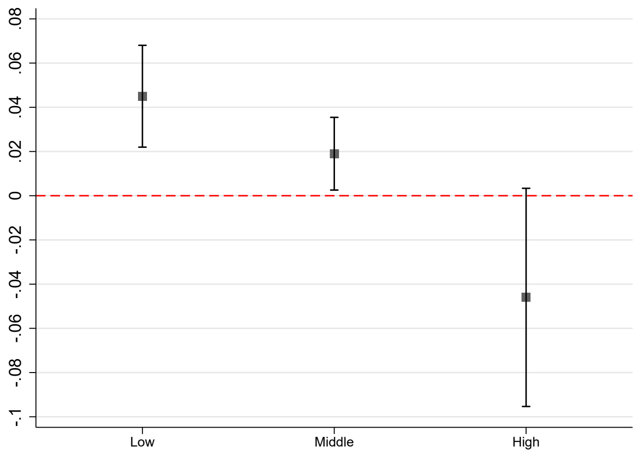


Panel B: Differential Effects Across Worker Pre-event Earnings

Figure 6. Heterogeneity of Effects by Pre-existing Inequality
The figure plots the differential effects of the ARLs on the earnings gap between minority and White workers by measures of pre-existing inequality within firms. The dependent variable is the logarithm of workers' average quarterly earnings in a year ($log(Earnings)$) from our Census LEHD-LBD sample. Panel A presents coefficient estimates for the interaction of $Treated \times Post \times Minority$ with indicators for different levels of pre-event earnings gap between White and minority workers within firms. Panel B reports the interactive coefficients with indicators for pre-event board demographic diversity, which is a linear combination of the standardized values of the share of female directors, the standard deviation of director ages, and the reversed Herfindahl-Hirschman Index (HHI) in ethnicity. In each panel, *Low*, *Middle*, and *High* represent indicators for the first, second, and third terciles of pre-event inequality, respectively. The dots in each panel indicate the point estimate of $Treated \times Post \times Minority$ interacted with each tercile indicator. The vertical lines represent the associated 90% confidence intervals. The coefficient estimates indicate the differential change in earnings for minority workers relative to White workers in each pre-existing inequality category. All regressions include the same controls as Column (5) of Table 3, including controls for worker tenure, event-firm-worker fixed effects, as well as interactions of year fixed effects with other worker characteristics and firm fixed effects. Standard errors are clustered by workers' state. Detailed variable definitions are provided in Appendix A.



Panel A: Differential Effects Across Pre-Existing Racial Pay Gap



Panel B: Differential Effects Across Board Demographic Diversity

Table 1
Summary Statistics

This table reports the summary statistics for the main variables used in our study. Panel A presents the average quarterly earnings, tenure, and worker demographics in the sample, constructed using Census LEHD-LBD data. Panel B reports summary statistics of job position changes, tenure, and worker demographics in the resume sample, constructed using Revelio resume data. Both samples span the period from 1990 through 2012. The LEHD-LBD sample includes 3,669,000 worker-year observations. The resume sample includes 34 million worker-year observations. All estimates and observation counts are rounded in accordance with Census disclosure rules. Detailed variable definitions are provided in Appendix A.

Panel A: Census LEHD-LBD Sample

Variable	Mean	St. Dev.
Earnings (in 2018Q3 $)	14670	16850
Log(Earnings)	9.35	0.68
Worker Age (in years)	40.49	10.98
Worker Tenure (in years)	5.94	4.56
Minority (in %)	14.8	35.5
Asian (in %)	4.43	20.6
Black (in %)	8.20	27.4
Other Minority (in %)	2.13	14.4
Male (in %)	56.6	49.6

Panel B: Revelio Resume Sample

Variable	Mean	St. Dev.
New Position (in %)	3.47	18.3
Promotion (in %)	3.49	18.3
Promotion Within Occ (in %)	1.45	12.0
Change to Tech-oriented (in %)	0.18	4.20
Worker Tenure (in years)	5.83	6.77
Minority (in %)	16.9	37.5
Male (in %)	63.8	48.1

Table 2
Racial Gap within Firms

This table examines various racial gaps using OLS model with different time-varying controls and fixed effects. The dependent variables include *Log(Earnings)*, the log of quarterly earnings, adjusted to 2018 Q3 dollars, averaged within a given year for each worker; *New Position*, an indicator for workers changing to a new position; *Promotion*, an indicator for workers changing to a new, higher-paid position; *Promotion Within Occ*, an indicator for workers being promoted to a new position in the same firm and with the same three-digit O*NET code; and *Change to Tech-oriented*, an indicator for workers switching to a tech-oriented position. All indicator outcome variables are multiplied by 100. *Minority* is a dummy variable for all workers who are non-White. Columns (1)-(2) use the Census LEHD-LBD sample, and columns (3)-(10) use the Revelio resume sample. Both samples are at the individual-year level, spanning from 1992 through 2012. It covers workers in treated and control firms. Treated firms refer to companies incorporated in LA (1997), TX (1997), and AL (2001). Control firms are those that are in the same 2-digit NAICS sector and employment size quintile as a treated firm, but are incorporated in states that never passed the laws. *Event* represents an indicator for a state passing the ARL. *Firm Char* include *Firm Age*, *Firm ROA*, *Firm Market/Book*, and *Firm Size*. *Worker Tenure* is a worker's total work tenure with a given employer. Event-Worker Char-year FE includes sex and education interacted with event-year fixed effects. Standard errors are clustered by workers' state and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively. Detailed variable definitions are provided in Appendix A.

Dep. Var.:	*Log(Earnings)*		*New Position*		*Promotion*		*Promotion Within Occ*		*Change to Tech-oriented*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Minority	-0.122***	-0.099***	-0.53***	-0.485***	-0.324***	-0.340***	-0.193***	-0.170***	-0.030***	-0.019***
	(0.019)	(0.010)	(0.059)	(0.044)	(0.048)	(0.038)	(0.026)	(0.021)	(0.007)	(0.004)
Event-Firm FE	Yes		Yes		Yes		Yes		Yes	
Event-Year FE	Yes		Yes		Yes		Yes		Yes	
Firm Char	Yes		Yes		Yes		Yes		Yes	
Event-Worker Char-Year FE		Yes		Yes		Yes		Yes		Yes
Event-State-Year FE		Yes		Yes		Yes		Yes		Yes
Event-Firm-Year FE		Yes		Yes		Yes		Yes		Yes
Worker Tenure		Yes		Yes		Yes		Yes		Yes
Observations	3,669,000	3,669,000	34,122,764	33,895,029	34,122,764	33,895,029	34,122,764	33,895,029	34,122,764	33,895,029
R-squared	0.301	0.451	0.0116	0.0220	0.0092	0.0187	0.0065	0.0154	0.0010	0.0062

Table 3
Access to Debt and Racial Earnings Gap Inside Firms
This table reports the change in the minority earnings gap post-treatment using a triple difference-in-difference model with different time-varying controls and fixed effects, where the dependent variable is *Log(Earnings)*, the log of quarterly earnings, adjusted to 2018 Q3 dollars, averaged within a given year for each worker. *Minority* is a dummy variable for all workers who are non-White. *Treat* is an indicator for workers working for parent companies incorporated in LA (1997), TX (1997), and AL (2001). The control group includes employees working for firms that are in the same 2-digit NAICS sector and quintile of employment size bin as a treated firm, but are incorporated in states that never passed the laws. *Post* is an indicator for years after the passage of the anti-recharacterization laws. *Firm Char* include *Firm Age*, *Firm ROA*, *Firm Market/Book*, and *Firm Size*. *Worker Tenure* is a worker's total work tenure with a given employer. Event-Worker Char-year FE includes minority, sex, and education fixed effects interacted with event-year fixed effects. *Treat* and *Treat×Minority* are absorbed by Event-Firm-Worker fixed effects. Coefficients on *Post×Minority* are estimated but not reported for brevity in specifications without Event-Minority-Year fixed effects (columns (1)-(2)), and are absorbed when Event-Minority-Year fixed effects are included (columns (3)-(5)). The underlying sample is the Census LEHD-LBD sample that spans from 1990 to 2012. Standard errors are clustered by workers' state and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively. Detailed variable definitions are provided in Appendix A.

Dep. Var.: *Log(Earnings)*	(1)	(2)	(3)	(4)	(5)
Treat×Post×Minority	0.052***	0.048***	0.045***	0.042***	0.032***
	(0.011)	(0.011)	(0.013)	(0.011)	(0.009)
Treat×Post	0.038	0.017	0.013	0.033*	
	(0.023)	(0.023)	(0.025)	(0.017)	
Event-Firm-Worker FE	Yes	Yes	Yes	Yes	Yes
Event-Year FE	Yes	Yes			
Firm Char		Yes	Yes	Yes	
Worker tenure			Yes	Yes	Yes
Event-Worker Char-Year FE			Yes	Yes	Yes
Event-Industry-Year FE				Yes	
Event-State-Year FE				Yes	Yes
Event-Firm-Year FE					Yes
Observations	3669000	3669000	3669000	3669000	3669000
R-squared	0.910	0.911	0.911	0.915	0.917

Table 4
Access to Debt and Earnings Changes Across Races

This table reports the change in the minority earnings gap using a triple difference-in-difference model with different time-varying controls and fixed effects, where the dependent variable is *Log(Earnings)*, the log of quarterly earnings, adjusted to 2018 Q3 dollars, averaged within a given year for each worker. *Asian* is an indicator for Asian, *Black* is an indicator for African American workers, and *Other Minority* includes American Indian or Alaska Native, Native Hawaiian or Other Pacific Islander, or multi-race group. *Treat* is an indicator for workers working for parent companies incorporated in LA (1997), TX (1997), and AL (2001). The control group includes employees working for parent companies that never experienced ARL, and in the same 2-digit NAICS sector and quintile of employment size bin with the parent companies of the treated workers. *Post* is an indicator for periods post the ARL. *Treat* and its interactions with *Asian*, *Black*, *Other Minority* are absorbed by event-firm-worker fixed effects. *Post×Asian*, *Post×Black*, and *Post×Other Minority* are estimated but not reported for brevity. *Firm Char* include *Firm Age*, *Firm ROA*, *Firm Market/Book*, and *Firm Size*. *Worker Tenure* is a worker's total work tenure with a given employer. Event-Worker Char-year FE includes minority, sex, and education fixed effects interacted with event-year fixed effects. *Treat* and *Treat×Minority* are absorbed by Event-Firm-Worker fixed effects. Coefficients on *Post×Minority* are estimated but not reported for brevity in specifications without Event-Minority-Year fixed effects, and are absorbed when Event-Minority-Year fixed effects are included. The underlying sample is the Census LEHD-LBD sample that spans from 1990 to 2012. Standard errors are clustered by workers' state and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively. Detailed variable definitions are provided in Appendix A.

Dep. Var.: *Log(Earnings)*	(1)	(2)	(3)	(4)	(5)
Treat×Post×Asian	0.061***	0.054***	0.051***	0.044***	0.025***
	(0.014)	(0.015)	(0.015)	(0.009)	(0.008)
Treat×Post×Black	0.059***	0.055***	0.051***	0.051***	0.043***
	(0.012)	(0.012)	(0.015)	(0.014)	(0.011)
Treat×Post×Other Minority	0.029**	0.027*	0.024*	0.015	0.009
	(0.013)	(0.013)	(0.013)	(0.011)	(0.010)
Treat×Post	0.038	0.017	0.013	0.034*	
	(0.023)	(0.023)	(0.025)	(0.016)	
Event-Firm-Worker FE	Yes	Yes	Yes	Yes	Yes
Event-Year FE	Yes	Yes			
Firm Char		Yes	Yes	Yes	
Worker tenure			Yes	Yes	Yes
Event-Worker Char-Year FE			Yes	Yes	Yes
Event-Industry-Year FE				Yes	
Event-State-Year FE				Yes	Yes
Event-Firm-Year FE					Yes
Observations	3669000	3669000	3669000	3669000	3669000
R-squared	0.910	0.911	0.911	0.915	0.917

Table 5
Access to Debt and Changes in Worker Career

This table reports the differential changes in the careers of minority and White workers, including having a new position, promotion, promotion within the occupation category, and changing to tech-oriented positions, following the passage of anti-recharacterization laws. The sample is an event-worker-year panel constructed using Revelio resume data. In Panel A, we examine the likelihood that a worker obtains a new position in the following year, i.e., *New Position*. In Panel B, we examine promotion rates, i.e., *Promotion*, defined as a worker changing to a new position with a higher salary. In Panel C, we further examine whether a worker is promoted to a new position in the same firm and with the same three-digit O*NET occupation code, i.e., *Promotion Within Occ*. Finally, in Panel D, we examine the likelihood that a worker changes to a tech-oriented occupation, i.e., *Change to Tech-oriented*. All outcome variables are multiplied by 100. *Treat* is an indicator for workers working for parent companies that incorporated in LA (1997), TX (1997), and AL (2001). The control group includes employees working for parent companies that never experienced ARL, and in the same 2-digit NAICS sector and quintile of employment size bin with the parent companies of the treated workers. *Post* is an indicator for periods post the ARL. *Minority* indicates whether a worker is non-White. *Firm Char* include *Firm Age*, *Firm ROA*, *Firm Market/Book*, and *Firm Size*. *Worker Tenure* is a worker's total work tenure with a given employer. Event-Worker Char-year FE includes minority, sex, and education interacted with event-year fixed effects. Occupation is defined based on three-digit O*NET occupation codes. For brevity, we only report estimates of our key variable of interest. Standard errors are clustered by workers' state and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively. Detailed variable definitions are provided in Appendix A.

Panel A: Having a New Position

Dep. Var.: *New Position* (%)	(1)	(2)	(3)	(4)	(5)
Treat×Post×Minority	0.286**	0.290**	0.276**	0.222**	0.196*
	(0.121)	(0.115)	(0.112)	(0.098)	(0.102)
Event-Firm FE	Yes	Yes	Yes	Yes	
Event-Year FE	Yes	Yes	Yes	Yes	
Firm Char		Yes	Yes		
Worker Tenure			Yes	Yes	Yes
Event-Worker Char-Year FE			Yes	Yes	Yes
Event-Occupation-Year FE				Yes	Yes
Event-State-Year FE				Yes	Yes
Event-Firm-Year FE					Yes
Observations	34,122,764	33,895,321	33,895,321	33,895,299	33,895,029
R-squared	0.0116	0.0116	0.0165	0.0199	0.0220

Panel B: Promotion

Dep. Var.: *Promotion* (%)	(1)	(2)	(3)	(6)	(7)
Treat×*Post*×*Minority*	0.319**	0.340***	0.306***	0.226**	0.195*
	(0.124)	(0.123)	(0.11)	(0.103)	(0.107)
Observations	34,122,764	33,895,321	33,895,321	33,895,299	33,895,029
R-squared	0.0092	0.0092	0.0138	0.0163	0.0187

Panel C: Promotion Within Occupation Category

Dep. Var.: *Promotion Within Occ* (%)	(1)	(2)	(3)	(6)	(7)
Treat×*Post*×*Minority*	0.179**	0.194***	0.195***	0.153**	0.153**
	(0.074)	(0.072)	(0.067)	(0.061)	(0.066)
Observations	34,122,764	33,895,321	33,895,321	33,895,299	33,895,029
R-squared	0.0065	0.0065	0.0097	0.0140	0.0154

Panel D: Change to Tech-Oriented Positions

Dep. Var.: *Change to Tech-oriented* (%)	(1)	(2)	(3)	(6)	(7)
Treat×*Post*×*Minority*	0.059***	0.051**	0.052**	0.047**	0.040*
	(0.020)	(0.020)	(0.02)	(0.02)	(0.02)
Observations	34,122,764	33,895,321	33,895,321	33,895,299	33,895,029
R-squared	0.0010	0.0010	0.0013	0.0048	0.0062
Event-Firm FE	Yes	Yes	Yes	Yes	
Event-Year FE	Yes	Yes	Yes	Yes	
Firm Char		Yes	Yes		
Worker Tenure			Yes	Yes	Yes
Event-Worker Char-Year FE			Yes	Yes	Yes
Event-Occupation-Year FE				Yes	Yes
Event-State-Year FE				Yes	Yes
Event-Firm-Year FE					Yes

Table 6
Access to Debt and Job Separation Rates and New Hire Pay Gap between Minority and White Workers

This table reports the differential changes between non-White and White workers in separation rates as well as new hires' earnings around the adoption of anti-recharacterization laws. In Panel A, the dependent variable is *Separation*, an indicator equal to one for worker-years if the worker is separated from their current employer in the next year. The sample includes workers in the Census LEHD-LBD data who separated from treated or control firms before or after the events. In Panel B, the dependent variable is *Log(New Hire Earnings)*, the logarithm of quarterly earnings, adjusted to 2018 Q3 dollars, averaged within a year for newly hired workers. The sample includes only new hires observed in the Census LEHD-LBD data, defined as workers who have been with a treated or control firm for less than a year, before or after the events. *Minority* is a dummy variable for all workers who are non-White, 0 otherwise. *Firm Char* includes *Firm Age*, *Firm ROA*, *Firm Market/Book*, and *Firm Size*. *Worker Tenure* is a worker's total work tenure with a given employer. Event-Worker Char-year FE includes minority, sex, and education interacted with event-year fixed effects. For brevity, we only report estimates of our key variable of interest. Standard errors are clustered by workers' state and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively. Detailed variable definitions are provided in Appendix A.

Panel A: Changes in Separation Rate Racial Gap Around ARLs

Dep. Var.: *Separation*	(1)	(2)	(3)	(4)	(5)
Treat×*Post*×*Minority*	-0.019	-0.014	-0.024	-0.013	0.002
	(0.027)	(0.026)	(0.030)	(0.021)	(0.008)
Observations	15770000	15770000	15770000	15770000	15770000
R-squared	0.057	0.058	0.077	0.111	0.143

Panel B: Changes in New Hire Earnings Gap Around ARLs

Dep. Var.: *Log(New Hire Earnings)*	(1)	(2)	(3)	(4)	(5)
Treat×*Post*×*Minority*	0.083**	0.083**	0.062**	0.063***	0.062**
	(0.040)	(0.039)	(0.028)	(0.022)	(0.023)
Observations	4777000	4777000	4777000	4777000	4777000
R-squared	0.398	0.399	0.448	0.459	0.475
Event-Firm FE	Yes	Yes	Yes	Yes	
Event-Year FE	Yes	Yes	Yes	Yes	
Firm Char		Yes	Yes	Yes	
Event-Worker Char-Year FE			Yes	Yes	Yes
Event-Industry-Year FE			Yes	Yes	
Event-State-Year FE			Yes	Yes	Yes
Event-Firm-Year FE					Yes

Table 7
Long Run Effects of Access to Debt on Racial Earnings Gap
This table reports the change in the minority earnings gap post-treatment using the triple difference-in-difference model. The dependent variable is *Log(Earnings)*, the logarithm of quarterly earnings, adjusted to 2018 Q3 dollars, averaged within a year. The sample includes workers' full employment records observed in the Census LEHD-LBD data, including years at both treated and control companies, as well as years at other employers afterward. *Minority* is an indicator variable for all non-White workers. *Treat* is an indicator for workers who worked for parent companies incorporated in LA (1997), TX (1997), and AL (2001). The control group includes employees who worked for parent companies that never experienced ARL, and in the same 2-digit NAICS sector and employment size quintile as the parent companies of the treated workers. *Post (Same Firm)* is an indicator for periods post the ARL but before the worker switched to another employer. *Post (Different Firm)* is an indicator for periods that the worker has moved to a new employer post the ARL. *Firm Char* include *Firm Age*, *Firm ROA*, *Firm Market/Book*, and *Firm Size*. *Worker Tenure* is a worker's total work tenure with a given employer. Event-Worker Char-year FE includes minority, sex, and education interacted with event-year fixed effects. For brevity, we only report estimates on our key variable of interest. Standard errors are clustered by workers' state and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively. Detailed variable definitions are provided in Appendix A.

Dep. Var.: *Log(Earnings)*	(1)	(2)	(3)	(4)	(5)
Treat×*Post (Same Firm)*×*Minority*	0.048***	0.049***	0.039***	0.003**	0.028***
	(0.008)	(0.009)	(0.010)	(0.012)	(0.008)
Treat×*Post (Different Firm)*×*Minority*	0.043**	0.045**	0.034*	0.032*	0.028
	(0.019)	(0.019)	(0.018)	(0.018)	(0.024)
Event-Worker FE	Yes	Yes	Yes	Yes	Yes
Event-Year FE	Yes	Yes			
Worker tenure		Yes	Yes	Yes	Yes
Event-Worker Char-Year FE			Yes	Yes	Yes
Event-State-Year FE				Yes	Yes
Event-Firm-Year FE					Yes
P-value (Same $\neq$ Different Firm)	0.80	0.83	0.70	0.93	0.98
Observations	6538000	6538000	6538000	6538000	6538000
R-squared	0.790	0.791	0.796	0.798	0.882

Table 8
External Validity Check: Short-term Debt Expiration Before the Global Financial Crisis
This table reports the changes in the earnings and promotion gap between minority and White workers for firms that faced financial constraints during the Global Financial Crisis. The dependent variable in column (1) is *Log(Earnings)*, the log of quarterly earnings, adjusted to 2018 Q3 dollars, averaged within a given year for each worker from LEHD-LBD. The dependent variables in columns (2)-(5) are from Revelio resume data, including *New Position*, an indicator for workers changing to a new position; *Promotion*, an indicator for workers changing to a new, higher-paid position; *Promotion Within Occ*, an indicator for workers being promoted to a new position in the same firm and with the same three-digit O*NET occupation code; and *Change to Tech-oriented*, an indicator for workers switching to a tech-oriented position. All indicator outcome variables are multiplied by 100. *Short-term Debt*$_{2007}$ is the net short-term debt normalized by book assets reported by July 2006 that matures in a year. It is constructed using Compustat data for U.S. publicly listed firms and standardized to have a mean of 0 and a standard deviation of 1. *Worker Tenure* is a worker's total work tenure with a given employer. Worker Char-year FE includes minority, sex, occupation (columns (2)-(5) only), and education, interacted with year fixed effects. For brevity, we only report estimates on our key variable of interest. Standard errors are clustered by firm and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively. Detailed variable definitions are provided in Appendix A.

Dep. Var.:	(1) *Log(Earnings)*	(2) *New Position*	(3) *Promotion*	(4) *Promotion Within Occ*	(5) *Change to Tech-Oriented*
Short-term Debt$_{2007}$ $\times$*Post*$_{2007}\times$ *Minority*	-0.003*** (0.001)	-0.008 (1.035)	-0.553 (1.385)	-0.358 (0.633)	-0.090 (0.304)
Firm-Worker-Year FE	Yes	Yes	Yes	Yes	Yes
Worker Tenure	Yes	Yes	Yes	Yes	Yes
Worker Char-Year FE	Yes	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes	Yes	Yes
Observations	10,100,000	597,808	597,808	597,808	597,808
R-squared	0.976	0.026	0.029	0.019	0.011

Table 9
Access to Debt and Changes in Earnings at Firms With and Without SPVs
This table reports the change in the earnings gap between minority and White workers for firms with and without SPVs. The dependent variable is *Log(Earnings)*, the log of quarterly earnings, adjusted to 2018 Q3 dollars, averaged within a given year for each worker. *Has SPV* (*No SPV*) is an indicator for whether a firm discloses at least one subsidiary (no subsidiary) in its 10-Ks during our sample period. *Treat* is an indicator for workers working for parent companies incorporated in LA (1997), TX (1997), and AL (2001). The control group includes employees working for parent companies that never experienced ARL, and in the same 2-digit NAICS sector and quintile of employment size bin as the parent companies of the treated workers. *Post* is an indicator for periods post the ARL. *Firm Char* include *Firm Age*, *Firm ROA*, *Firm Market/Book*, and *Firm Size*. *Worker Tenure* is a worker's total work tenure with a given employer. Event-Worker Char-year FE includes minority, sex, and education interacted with event-year fixed effects. For brevity, we only report estimates on our key variable of interest. The underlying sample is the Census LEHD-LBD sample that spans from 1990 to 2012. Standard errors are clustered by workers' state and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively. Detailed variable definitions are provided in Appendix A.

Dep. Var.: *Log(Earnings)*	(1)	(2)	(3)	(4)	(5)
Treat×*Post*×*Minority*×*No SPV*	0.017	0.01	0.013	-0.009	-0.001
	(0.021)	(0.019)	(0.020)	(0.012)	(0.016)
Treat×*Post*×*Minority*×*Has SPV*	0.059***	0.055***	0.050***	0.047***	0.035***
	(0.013)	(0.014)	(0.017)	(0.012)	(0.010)
Event-Firm-Worker FE	Yes	Yes	Yes	Yes	Yes
Event-Year FE	Yes	Yes			
Firm Controls		Yes	Yes	Yes	
Worker Tenure		Yes	Yes	Yes	Yes
Event-Worker Char-Year FE			Yes	Yes	Yes
Event-Industry-Year FE				Yes	
Event-State-Year FE				Yes	Yes
Event-Firm-Year FE					Yes
Observations	3669000	3669000	3669000	3669000	3669000
R-squared	0.91	0.911	0.911	0.915	0.917

Table 10
Robustness Checks
This table reports the results of robustness checks for our empirical specification. In Panel A, we examine the effect of the anti-recharacterization laws on workers' pay rank inside the firm. *Pay Rank* is a 1-100 index representing the percentile ranking of a worker's pay inside the firm. In Panels B-D, the dependent variable is *Log(Earnings)*, the log of quarterly earnings, adjusted to 2018 Q3 dollars, averaged within a given year for each worker. In Panel B, we re-estimate Equation (4) by assigning treated firms to be untreated after 2003. *Treat (on-off)* is an indicator that turns to one for individuals working in companies that are incorporated in LA (1997), TX (1997), and AL (2001), after those states passed the anti-recharacterization laws, but no later than 2003. This indicator turns to zero for treated individuals in years after 2003, and also for control observations. In Panel C, we cluster standard errors by firms' state of incorporation. In Panel D, we restrict the sample to individuals with non-imputed race. In each panel, *Minority* is an indicator variable for all non-White workers. *Firm Char* include *Firm Age*, *Firm ROA*, *Firm Market/Book*, and *Firm Size*. *Worker Tenure* is a worker's total work tenure with a given employer. Event-Worker Char-year FE includes minority, sex, and education interacted with event-year fixed effects. For brevity, we only report estimates on our key variable of interest. The underlying sample is the Census LEHD-LBD sample that spans from 1990 to 2012. Standard errors (except for Panel C) are clustered by workers' state and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively. Detailed variable definitions are provided in Appendix A.

Panel A: Changes in Racial Pay Rank Gap Around ARL

Dep. Var.: *Pay Rank*	(1)	(2)	(3)	(4)	(5)
Treat×Post×Minority	1.962**	2.028**	2.640***	1.946***	1.453**
	(0.795)	(0.780)	(0.935)	(0.586)	(0.524)
Treat×Post	-2.529	-2.485	-2.728	0.713	
	(1.491)	(1.705)	(1.690)	(1.020)	
Event-Firm-Worker FE	Yes	Yes	Yes	Yes	Yes
Event-Year FE	Yes	Yes			
Firm Char		Yes	Yes	Yes	
Worker tenure			Yes	Yes	Yes
Event-Worker Char-Year FE			Yes	Yes	Yes
Event-Industry-Year FE				Yes	
Event-State-Year FE				Yes	Yes
Event-Firm-Year FE					Yes
Observations	3669000	3669000	3669000	3669000	3669000
R-squared	0.862	0.862	0.863	0.886	0.903

Panel B: Excluding Post-2003 Years From Treatment

Dep. Var.: *Log(Earnings)*	(1)	(2)	(3)	(4)	(5)
Treat (on-off)×Post×Minority	0.034***	0.030**	0.026*	0.023**	0.016*
	(0.012)	(0.012)	(0.013)	(0.011)	(0.009)
Event-Firm-Worker FE	Yes	Yes	Yes	Yes	Yes
Event-Year FE	Yes	Yes			
Firm Char		Yes	Yes	Yes	
Worker tenure			Yes	Yes	Yes
Event-Worker Char-Year FE			Yes	Yes	Yes
Event-Industry-Year FE				Yes	
Event-State-Year FE				Yes	Yes
Event-Firm-Year FE					Yes
Observations	3669000	3669000	3669000	3669000	3669000
R-squared	0.911	0.911	0.912	0.915	0.918

Panel C: Clustering by States of Incorporation

Dep. Var.: *Log(Earnings)*	(1)	(2)	(3)	(4)	(5)
Treat×Post×Minority	0.052***	0.048***	0.045***	0.042***	0.032***
	(0.010)	(0.011)	(0.011)	(0.011)	(0.010)
Event-Firm-Worker FE	Yes	Yes	Yes	Yes	Yes
Event-Year FE	Yes	Yes			
Firm Char		Yes	Yes	Yes	
Worker tenure			Yes	Yes	Yes
Event-Worker Char-Year FE			Yes	Yes	Yes
Event-Industry-Year FE				Yes	
Event-State-Year FE				Yes	Yes
Event-Firm-Year FE					Yes
Observations	3669000	3669000	3669000	3669000	3669000
R-squared	0.91	0.911	0.911	0.915	0.917

Panel D: Using Non-imputed Race

Dep. Var.: *Log(Earnings)*	(1)	(2)	(3)	(4)	(5)
Treat×Post×Minority	0.054***	0.049***	0.047***	0.044***	0.034***
	(0.012)	(0.012)	(0.014)	(0.012)	(0.010)
Event-Firm-Worker FE	Yes	Yes	Yes	Yes	Yes
Event-Year FE	Yes	Yes			
Firm Char		Yes	Yes	Yes	
Worker tenure			Yes	Yes	Yes
Event-Worker Char-Year FE			Yes	Yes	Yes
Event-Industry-Year FE				Yes	
Event-State-Year FE				Yes	Yes
Event-Firm-Year FE					Yes
Observations	3484000	3484000	3484000	3484000	3484000
R-squared	0.911	0.912	0.912	0.916	0.918

Table 11
Separating Effects by Immigrants and Sex
This table reports differential effects of the anti-recharacterization laws on worker earnings by different demographics among minority workers relative to White workers' earnings. In both panels, the dependent variable is *Log(Earnings)*. In Panel A, we separately estimate the effects for minority immigrants and U.S.-born workers by interacting $Treat \times Post$ with two indicators: *Minority (Immigrants)*, an indicator equal to one for non-U.S.-born and non-White workers, and zero otherwise; *Minority (U.S.-Born)*, an indicator equal to one for U.S.-born and non-White workers, and zero otherwise. In Panel B, we separately estimate the differential effects for female and male minority workers by interacting $Treat \times Post$ with two indicators: *Minority Female*, An indicator equal to one for non-White female workers, and zero otherwise; *Minority Male*, an indicator equal to one for non-White male workers, and zero otherwise. *Firm Char* include *Firm Age*, *Firm ROA*, *Firm Market/Book*, and *Firm Size*. *Worker Tenure* is a worker's total work tenure with a given employer. Event-Worker Char-year FE includes minority, sex, and education interacted with event-year fixed effects. For brevity, we only report estimates on our key variable of interest. Standard errors are clustered by workers' state and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively. Detailed variable definitions are provided in Appendix A.

Panel A: Separating Effects for Immigrants and U.S. Born Workers

Dep. Var.: *Log(Earnings)*	(1)	(2)	(3)
Treat×Post×Minority (Immigrants)	0.070***	0.058***	0.042***
	(0.016)	(0.017)	(0.015)
Treat×Post×Minority (U.S.-Born)	0.049***	0.043***	0.031**
	(0.011)	(0.013)	(0.012)
Event-Firm-Worker FE	Yes	Yes	Yes
Event-Year FE	Yes		
Firm Char		Yes	
Worker tenure		Yes	Yes
Event-Worker Char-Year FE		Yes	Yes
Event-Industry-Year FE			
Event-State-Year FE			Yes
Event-Firm-Year FE			Yes
P-value (Immigrants = US Born)	0.2022	0.2511	0.6038
Observations	3669000	3669000	3669000
R-squared	0.91	0.911	0.917

Panel B: Separating Effects for Female and Male Workers

Dep. Var.: *Log(Earnings)*	(1)	(2)	(3)
Treat×Post×Minority Female	-0.01	-0.017	-0.020*
	(0.014)	(0.014)	(0.011)
Treat×Post×Minority Male	0.098***	0.090***	0.070***
	(0.012)	(0.015)	(0.014)
Event-Firm-Worker FE	Yes	Yes	Yes
Event-Year FE	Yes		
Firm Char		Yes	
Worker tenure		Yes	Yes
Event-Worker Char-Year FE		Yes	Yes
Event-State-Year FE			Yes
Event-Firm-Year FE			Yes
Observations	3669000	3669000	3669000
R-squared	0.91	0.911	0.918

Appendix A Variable Definitions

- *Earnings*: The quarterly earnings, adjusted to 2018 Q3 dollars, averaged across quarters within a given year for a given worker. Source: LEHD
- *Log(Earnings)*: The log of the average quarterly earnings (in 2018Q3 dollars) across quarters within a year for a given worker. Source: LEHD-LBD
- *Minority*: An indicator equal to one for non-White workers, and zero otherwise. Source: LEHD/Revelio
- *Black*: An indicator equal to one if a worker's reported race is Black or African-American, and zero otherwise. Source: LEHD
- *Asian*: An indicator equal to one if a worker's reported race is Asian or Native Hawaiian, Other Pacific Islander, and zero otherwise. Source: LEHD
- *Other Minority*: An indicator equal to one if a worker's reported race is American Indian, Alaska Native, or workers with two or more race groups, and zero otherwise. Source: LEHD
- *Worker Age*: The number of years between current year and a worker's birth year. Source: LEHD
- *Worker Tenure*: The number of years a worker has worked for their employee. Source: LEHD-LBD
- *Male*: An indicator equal to one for male workers, and zero otherwise. Source: LEHD
- *New Position*: An indicator that equals one if a worker obtains a new position within the same firm in the following year, and zero otherwise. This indicator is multiplied by 100 in regressions. Source: Revelio
- *Promotion*: An indicator that equals one if a worker changes to a new position with a higher salary next year, and zero otherwise. This indicator is multiplied by 100 in regressions. Source: Revelio
- *Promotion Within Occ*: An indicator that equals one if a worker changes to a new position with a higher salary in the same firm and the same three-digit O*NET code next year, and zero otherwise. This indicator is multiplied by 100 in regressions. Source: Revelio
- *Change to Tech-oriented*: An indicator that equals one if a worker changes to a tech-oriented occupation next year, and zero otherwise. This indicator is multiplied by 100 in regressions. Following Hecker (2005), tech-oriented occupations include scientific, engineering, and technician occupations: computer and mathematical scientists, Standard Occupational Classification (SOC) 15-0000; engineers, SOC 17-2000; drafters, engineering, and mapping technicians, SOC 17-3000; life scientists, SOC 19-1000; physical scientists, SOC 19-2000; life, physical, and social science technicians, SOC 19-4000; computer and information systems managers, SOC 11-3020; engineering managers, SOC 11-9040; and natural sciences managers, SOC 11-9120. Source: Revelio
- *Treat*: An indicator equal to one for workers working for parent companies incorporated in LA (1997), TX (1997), and AL (2001), and zero for individuals working in control firms. Source: LEHD-LBD/Revelio and Compustat
- *Post*: An indicator equal to one for periods post the treatment (passage of the ARL in a given incorporation state), 0 otherwise. Source: LEHD-LBD/Revelio and Compustat

- *Firm Age*: Age of a firm, defined as the difference between the current year and the first year the firm is observed in LBD with positive employment. Source: LBD
- *Firm ROA*: Return on asset, defined as net income scaled by total assets. Source: Compustat
- *Firm Market/Book*: Source: Compustat
- *Firm Size*: The log of total assets. Source: Compustat
- *High/Mid/Low Skill*: An indicator equal to one if a worker's *Earnings* in the year prior to the event year is in the top/middle/bottom tercile of the sample distribution. Source: LEHD-LBD
- *Low/Mid/High Pre-event Earnings Gap*: An indicator equal to one for employers whose racial earnings gap is ranked in the bottom/middle/top tercile during the year prior to the event year, and zero otherwise. Source: LEHD-LBD
- *Low/Mid/High Board Diversity* An indicator equal to one for employers whose board diversity is ranked in the bottom/middle/top tercile during the year prior to the event year, and zero otherwise. For a given firm-year, following Bernile et al. (2018), this index is calculated as Std. Age + Share of female directors - Ethnicity HHI, where each factor is normalized to have zero mean and standard deviation of one. Std. Age is the standard deviation of the ages of the board directors at a given firm-year. Ethnicity HHI is equal to the sum of the squares of director ethnicity shares within the board of a given firm-year. Ethnic categories, as defined in RiskMetrics, include Asian, African-American, Caucasian, Hispanic, and Native American. Source: LEHD-LBD, BoardEx, and RiskMetrics
- *Low/Mid/High White Worker Share*: An indicator equal to one for workers located in commuting zones where the percentage of White workers is ranked in the bottom/middle/top tercile during the year prior to the event year, and zero otherwise. Source: LEHD
- *Low/Mid/High Unemployment Rate*: An indicator equal to one for workers located in commuting zones where the unemployment rate is ranked in the bottom/middle/top tercile during the year prior to the event year, and zero otherwise. Source: LEHD and Bureau of Labor Statistics
- *Separation*: An indicator equal to one for worker-years if the worker separates with the current employer in the following year, and zero otherwise. Source: LEHD-LBD
- *Log(New Hire Earnings)*: The log of the average quarterly earnings (in 2018Q3 dollars) across quarters within a year for newly hired workers who have been with the employer for less than a year. Source: LEHD-LBD
- *Post (Same Firm)* is an indicator for periods post the ARL but before the worker switched to another employer. Source: LEHD-LBD
- *Post (Different Firm)* is an indicator for periods that the worker has moved to a new employer post the ARL. Source: LEHD-LBD
- *Short-term Debt*$_{2007}$ is defined following Duchin et al. (2010) as the net short-term debt normalized by book assets reported by July 2006 that matures in a year, i.e., *Short-term Debt*$_{2007}$ = (short-term debt + long-term debt maturing in less than one year − cash and cash equivalents) / total book assets. It is standardized to have a mean of 0 and a standard deviation of 1. Source: Compustat
- *Post*$_{2007}$ is an indicator for years 2007 and 2008, and zero for 2006. Source: LEHD-LBD
- *No/Has SPV*: An indicator for whether a firm discloses at least one subsidiary (no subsidiary) in its 10-Ks during our sample period (1990-2012). Source: SEC 10-Ks

- *Pay Rank*: The percentile of a worker's average quarterly earnings ranked within a firm year. It equals 100×(the rank of employee's *Earnings* within a given firm-year divided by the number of employees of a given firm-year). Source: LEHD-LBD
- *Treat (on-off)*: An indicator equal to one for employment years before (including) 2003 of individuals working for parent companies that incorporated in AL (2001), TX (1997), and LA (1997), and zero for all other observations of those workers as well as for workers in the control group. Source: LEHD-LBD and Compustat
- *Minority (Immigrants)*: An indicator equal to one for non-U.S.-born and non-White workers, and zero otherwise. Source: LEHD
- *Minority (U.S.-Born)*: An indicator equal to one for U.S.-born and non-White workers, and zero otherwise. Source: LEHD
- *Minority Female*: An indicator equal to one for non-White female workers, and zero otherwise. Source: LEHD
- *Minority Male*: An indicator equal to one for non-White male workers, and zero otherwise. Source: LEHD

Appendix B Additional Analyses

Table D.1
ARLs, Leverage, and Employment
This table reports the effects of ARLs on leverage and employment. The dependent variables are firm-level *Leverage* from Compustat in Panel A, and *Log(Emp)*, the log of plant-level employment, from Census LBD in Panel B. *Treat* is an indicator for companies that incorporated in LA (1997), TX (1997), and AL (2001). The control group includes firms that never experienced ARL, in the same 2-digit NAICS sector and employment size quintile as the treated firms. In Panel A, *Firm Char* includes *Log(Sales)*, *Profitability*, *Tobin's Q*, and *Tangibility*, consistent with the prior literature (Li et al., 2016; Ersahin, 2020). In Panel B, *Firm Char* includes *Log(Sales)*, *Profitability*, and *Tobin's Q*. State and industry represent state and industry plants that operate in. Standard errors are clustered by firm in Panel A and by plant in Panel B. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: Firm Leverage

Dep. Var.: *Leverage*	(1)	(2)
Treat×Post	0.043**	0.038**
	(0.018)	(0.017)
Event-Firm FE	Yes	Yes
Event-Year FE	Yes	Yes
Firm Char		Yes
Observations	97694	94974
R-squared	0.606	0.649

Panel B: Plant Employment

Dep. Var.: *Log(Emp)*	(1)	(2)	(3)	(4)
Treat×Post	0.086***	0.076***	0.062***	0.063***
	(0.019)	(0.024)	(0.018)	(0.019)
Event-Plant FE	Yes	Yes	Yes	Yes
Event-Year FE	Yes	Yes		
Firm Controls		Yes	Yes	Yes
Event-State-year FE			Yes	Yes
Event-Industry-year FE				Yes
Observations	2576000	2576000	2576000	2576000
R-squared	0.917	0.918	0.918	0.921

Access to Financing and Racial Pay Gap Inside Firms

Janet Gao, Wenting Ma and Qiping Xu

INTERNET APPENDIX

I Detailed Model

I.1 Model Setup and Notation

This is a one-period model involving one firm's decision to allocate workers to positions/tasks during time t. After job allocation is done, production starts. The firm distributes all profit as dividends and is dissolved in $t+1$. To finance its production, the firm uses its internal resources N (i.e., net worth) and borrows D. Cost of debt financing is R, assumed to be fixed in a competitive credit market.

There are two tasks inside the firm. Task 1 requires some training and skill, while Task 2 does not. For simplicity, assume each task only requires human capital input: L_1 and L_2. One can consider Task 1 to represent complex, non-routine jobs that require managerial, analytical, and/or interpersonal skills, and Task 2 to represent jobs with low skill content. The firm's production follows the standard CES function $(\alpha L_1^\rho + \beta L_2^\rho)^{1/\rho}$, where $\rho \leq 1$ and $0 < \beta < \alpha < 1$. Thus, Task 1 is more productive for the firm than Task 2.

The firm can utilize White or minority workers for either task. We denote the amount of White (minority) workers performing Task 1 as $l_1^{(w)}$ ($l_1^{(m)}$), and the number of White (minority) workers performing Task 2 as $l_2^{(w)}$ ($l_2^{(m)}$). So $L_1 = l_1^{(w)} + l_1^{(m)}$ and $L_2 = l_2^{(w)} + l_2^{(m)}$

Lastly, we use ω_i to denote the market wages for workers performing Task i ($i = 1, 2$). The firm is a price-taker in this market. However, it needs to provide resources to train workers before they can perform each task, so the effective labor cost is the sum of wages and training cost (c). For White workers in Task i, the effective cost is is $C_i^{(w)} = \omega_i^{(w)} l_i^{(w)} + c(l_i^{(w)})$, and the effective labor cost for hiring a minority worker in Task i is $C_i^{(m)} = \omega_i^{(m)} l_i^{(m)} + c(l_i^{(m)})$. Here, c represents the training costs, which is a function of the workers being hired.

The training cost for both White and nonwhite workers have a positive slope: $c(l) = al + c$, where $a > 0$ represents the speed with which training cost increases with worker quantity. Higher values of a indicate greater scarcity. $c > 0$ represents the minimum training cost. $0 < c_w < c_m$ and $a_w > a_m$.

For the unskilled task (Task 2), we do not make differential assumptions between White and minority workers. Thus for simplicity, we can use a_2 and c_2 to denote the slope and intercept of the training cost function for both racial groups performing Task 2.

Based on the setup above, we can write the following cost functions for White and minority workers used for Task 1 and 2:

$$
\begin{aligned}
C_1^{(w)} &= \omega_1 l_1^{(w)} + (a_w l_1^{(w)} + c_w) l_1^{(w)} \\
C_1^{(m)} &= \omega_1 l_1^{(m)} + (a_m l_1^{(m)} + c_m) l_1^{(m)} \\
C_2^{(w)} &= \omega_2 l_2^{(w)} + (a_2 l_2^{(w)} + c_2) l_1^{(w)} \\
C_2^{(m)} &= \omega_2 l_2^{(m)} + (a_2 l_2^{(m)} + c_2) l_2^{(m)}
\end{aligned}
$$

I.2 The Firm's Optimization Problem

The firm solves for the optimal labor decisions $\{l_1^{(w)}, l_1^{(m)}, l_2^{(w)}, l_2^{(m)}\}$, and borrowing decision D by maximizing the following production function:

$$max_{\{l_1^{(w)}, l_1^{(m)}, l_2^{(w)}, l_2^{(m)}, D\}} (\alpha(l_1^{(w)} + l_1^{(m)})^\rho + \beta(l_2^{(w)} + l_2^{(m)})^\rho)^{1/\rho} - RD \tag{9}$$

$$s.t.\ \ C_1^{(w)} + C_1^{(m)} + C_2^{(w)} + C_2^{(m)} \leq N + D....(\lambda) \tag{10}$$

Suppose the marginal worker is White. The first order condition w.r.t. $l_1^{(w)}$ is the following:

$$\alpha X^{1/\rho - 1}(l_1^{(w)} + l_1^{(m)})^{\rho - 1} \geq \lambda(2a_w l_1^{(w)} + \omega_1 + c_w)$$

where $X = \alpha L_1^\rho + \beta L_2^\rho$.

Analogously, if the marginal worker is non-White, the first order condition w.r.t. $l_1^{(b)}$ is the following:

$$\alpha X^{1/\rho - 1}(l_1^{(w)} + l_1^{(m)})^{\rho - 1} \geq \lambda(2a_m l_1^{(m)} + \omega_1 + c_m)$$

Given that the training costs for White workers are lower than those for non-White workers, i.e., $c_w < c_m$, this means that $C_1^{(w)}(0) < C_1^{m}(0)$. In other words, initially, it is less costly to use White workers to perform Task 1. The firm thus prioritizes using White workers for Task 1. This helps explain why racial wage gap exists inside the firm. The firm only starts using non-White workers for Task 1 when the marginal cost of using White workers becomes exceedingly high.

Lemma 1 *There exists a threshold l_1^*, such as when the firm needs more skilled workers than this threshold, it will start utilizing non-White workers. l_1^* satisfies:*

$$l_1^* = \frac{c_m - c_w}{2a_w} = \frac{\Delta c}{2a_w} \tag{11}$$

Here, $\Delta c = c_m - c_w$. l_1^* is the amount of White workers for which the marginal cost of using one additional White worker equals the marginal cost of using a non-zero amount of minority worker. Below this threshold, the marginal cost of using a White worker is $MC = 2a_w l_1^{(w)} + \omega_1 + c_w < \omega_1 + c_m$. Thus, the marginal cost of using an additional White worker is smaller than the marginal cost of starting to use a non-White worker.

Above this threshold, both White and non-White workers are marginal workers. So their marginal cost should equalize. In other words, the number of White and non-White workers performing Task 1 satisfies:

$$2a_w l_1^{(w)} + c_w = 2a_m l_1^{(m)} + c_b$$

or

$$l_1^{(w)} = \frac{a_m}{a_w} l_1^{(m)} + \Delta c \tag{12}$$

This means that, when the firm increases its labor demand for Task 1, it will increase both White and non-White workers. However, it increases the utilization of non-White workers more than White workers, since it faces a steeper supply curve of skilled White workers (i.e., $\frac{a_m}{a_w} < 1$).

Next, we derive the F.O.C. for low-skill labor $l_2^{(w)}$ and $l_2^{(m)}$:

$$\beta X^{1/\rho - 1} L_2^{\rho - 1} = \lambda(2a_2 l_2^{(w)} + \omega_2 + c_2)$$

$$\beta X^{1/\rho - 1} L_2^{\rho - 1} = \lambda(2a_2 l_2^{(m)} + \omega_2 + c_2)$$

From the above equations, it is easy to see it is a symmetric decision to hire White and minority workers to perform Task 2, so $l_2^{(w)} = l_2^{(m)}$, i.e., the firm allocates the same number of White and non-White workers for the low-skill job.

From the F.O.C. of debt amount D, we have $\lambda = R$.

Lemma 2 *Low-skill labor L_2 is a linear function of skilled labor $l_1^{(b)}$*

$$l_2^{(w)} = l_2^{(m)} = A l_1^{(m)} + B \tag{13}$$

Where $A := \left(\frac{\alpha}{\left(\frac{R(2a_2 l_2^{(m)} + \omega_2 + c_2)}{\beta}\right)^{\frac{\rho}{1-\rho}} - \beta}\right)^{\frac{1}{\rho}} \left(\frac{a_w + a_m}{2a_w}\right)$ *and* $B := \left(\frac{\alpha}{\frac{R(2a_2 l_2^{(m)} + \omega_2 + c_2)}{\beta} - \beta}\right)^{\frac{1}{\rho}} \frac{\Delta c}{2}$.

Proof:

From the F.O.C. of low-skill labor, we have

$$X^{(1-\rho)/\rho} = \frac{R(2a_2 l_2^{(m)} + \omega_2 + c_2)}{\beta} L_2^{1-\rho}$$

So

$$X = \left(\frac{R(2a_2 l_2^{(m)} + \omega_2 + c_2)}{\beta}\right)^{\frac{\rho}{1-\rho}} L_2^{\rho}$$

We also have:

$$X = \alpha L_1^{\rho} + \beta L_2^{\rho} = \alpha\left[\frac{a_w + a_m}{a_w} l_1^{(b)} + \Delta c)\right]^{\rho} + \beta L_2^{\rho}$$

Combining the above two equations, we have

$$((\frac{R}{\beta}(2a_2l_2^{(m)}+\omega_2+c_2))^{\frac{\rho}{1-\rho}}-\beta)^{\frac{1}{\rho}}L_2=\alpha^{\frac{1}{\rho}}L_1=\alpha^{\frac{1}{\rho}}(\frac{a_w+a_m}{a_w}l_1^{(m)}+\Delta c)$$

Given that $L_2=2l_2^{(m)}$, we have

$$l_2^{(m)}=l_2^{(w)}=(\frac{\alpha}{(\frac{R(2a_2l_2^{(m)}+\omega_2+c_2)}{\beta})^{\frac{\rho}{1-\rho}}-\beta})^{\frac{1}{\rho}}(\frac{a_w+a_m}{2a_w})l_1^{(m)}+(\frac{\alpha}{\frac{R(2a_2l_2^{(m)}+\omega_2+c_2)}{\beta}-\beta})^{\frac{1}{\rho}}\frac{\Delta c}{2}$$

We denote $A:=(\frac{\alpha}{(\frac{R(2a_2l_2^{(m)}+\omega_2+c_2)}{\beta})^{\frac{\rho}{1-\rho}}-\beta})^{\frac{1}{\rho}}(\frac{a_w+a_m}{2a_w})$ and $B:=(\frac{\alpha}{\frac{R(2a_2l_2^{(m)}+\omega_2+c_2)}{\beta}-\beta})^{\frac{1}{\rho}}\frac{\Delta c}{2}$, then $l_2^{(m)}=Al_1^{(m)}+B$.

Q.E.D.

Recall the assumption:

Assumption 1 $R(\omega_2+c_2)\geq max\{\beta^{\frac{1}{\rho}},\beta^2\}$.

Under this condition, both A and B take positive values and are decreasing functions of l_2^m. See proof below:

Under the parameter restriction, $R(\omega_2+c_2)\geq\beta^{\frac{1}{\rho}}$, we have $(\frac{R}{\beta}(2a_2l_2^{(m)}+\omega_2+c_2))^{\frac{\rho}{1-\rho}}-\beta\geq 0,\forall l_2^{(m)}\geq 0$. Thus A always takes positive values.

For B to take positive values, we need $\frac{R(2a_2l_2^{(m)}+\omega_2+c_2)}{\beta}\geq\beta$, and a sufficient condition for that is $R(\omega_2+c_2)\geq\beta^2$.

Q.E.D.

Also, we note that both A and B are declining functions of $l_2^{(m)}$.

I.3 Access to Financing and Racial Wage Gap

We analyze how changes in the cost of financing (R) affect the firm's utilization of non-White workers for the skilled task (i.e., Task 1) and the racial pay gap inside the firm.

Proposition 1 *The number of skilled workers L_1 decreases with R, the cost of financing. When $L_1>l_1^*$, the number of skilled minority workers $l_1^{(m)}$ decreases with R. The number of unskilled workers $l_2^{(m)}$ (and $l_2^{(w)}$) decreases with R.*

Proof:

As discussed before, when the demand for skilled workers is relatively low, i.e., $L_1<l_1^*$, the firm does not utilize any non-White worker for Task 1. We now analyze the case where $L_1\geq l_1^*$. In this case, non-White workers are the marginal worker, so the first-order-condition can be written as:

$$F=\alpha X^{1/\rho-1}(l_1^{(w)}+l_1^{(m)})^{\rho-1}-R(2a_ml_1^{(m)}+\omega_1+c_m)=0 \tag{14}$$

The Envelope Theorem suggests that

$$\frac{\partial l_1^{(m)}}{\partial\lambda}=-\frac{\partial F/\partial R}{\partial F/\partial l_1^{(m)}}$$

$$-\partial F/\partial R=2a_ml_1^{(m)}+\omega_1+c_m>0$$

$$\begin{aligned}\partial F/\partial l_1^{(m)}&=\alpha(1/\rho-1)X^{1/\rho-2}\alpha\rho L_1^{\rho-1}L_1^{\rho-1}+\alpha X^{1/\rho-1}(\rho-1)L_1^{\rho-2}-2Ra_m\\&=\alpha X^{1/\rho-2}L_1^{\rho-2}((1-\rho)\alpha L_1^{\rho}+X(\rho-1))-2Ra_m\\&=\alpha X^{1/\rho-2}L_1^{\rho-2}(1-\rho)(\alpha L_1^{\rho}-X)-2Ra_m<0\end{aligned}$$

Thus $\frac{\partial l_1^{(m)}}{\partial R} < 0$, meaning that the utilization of minority workers for the skilled task decreases with R, the cost of financing. This means that as the cost of financing declines, firms utilizes more minority workers.

Similarly, the F.O.C. for low-skill minority workers is:

$$G = \beta X^{1/\rho-1} L_2^{\rho-1} - R(2a_2 l_2^{(m)} + \omega_2 + c_2) = 0 \tag{15}$$

According to the Envelope Theorem:

$$\frac{\partial l_2^{(m)}}{\partial \lambda} = -\frac{\partial G/\partial R}{\partial G/\partial l_2^{(m)}}$$

$$\begin{aligned}
\partial G/\partial l_2^{(m)} &= \beta(1/\rho - 1) X^{1/\rho-2} \beta\rho L_2^{\rho-1} L_2^{\rho-1} + \beta X^{1/\rho-1}(\rho-1) L_2^{\rho-2} - 2Ra_2 \\
&= \beta X^{1/\rho-2} L_2^{\rho-2}((1-\rho)\beta L_2^{\rho} + X(\rho-1)) - 2Ra_2 \\
&= \beta X^{1/\rho-2} L_2^{\rho-2}(1-\rho)(\beta L_2^{\rho} - X) - 2Ra_2 < 0
\end{aligned}$$

Thus $\frac{\partial l_2^{(m)}}{\partial R} < 0$, i.e., the number of minority workers for the low-skill task decreases with R.
Q.E.D.

This proposition suggests that with better access to debt, firms can allocate more human capital to skilled, productive tasks. They start by utilizing solely White workers, until the marginal costs become too high. As R continues to decline, firms allocate more and more non-White workers to the skilled task.

Next, we analyze how the racial pay gap inside the firm changes with R. The racial pay gap is the difference between the average pay for White workers and the average pay for non-White workers, $\bar{\omega}_w - \bar{\omega}_m$.

The average wage for White workers is

$$\bar{\omega}_w = \frac{l_1^{(w)}\omega_1 + l_2^{(w)}\omega_2}{l_1^{(w)} + l_2^{(w)}} = \omega_1 + \frac{l_2^{(w)}(\omega_2 - \omega_1)}{l_1^{(w)} + l_2^{(w)}}$$

The average wage for non-White workers is

$$\bar{\omega}_m = \frac{l_1^{(m)}\omega_1 + l_2^{(m)}\omega_2}{l_1^{(m)} + l_2^{(m)}} = \omega_1 + \frac{l_2^{(m)}(\omega_2 - \omega_1)}{l_1^{(m)} + l_2^{(m)}}$$

Proposition 2 *Within-firm racial pay gap $\bar{\omega}_w - \bar{\omega}_m$ is an increasing function of the cost of financing, R.*

Proof:

We can write within-firm wage gap as

$$\begin{aligned}
\bar{\omega}_w - \bar{\omega}_m &= \frac{l_2^{(m)}(\omega_2 - \omega_1)}{l_1^{(w)} + l_2^{(m)}} - \frac{l_2^{(m)}(\omega_2 - \omega_1)}{l_1^{(m)} + l_2^{(m)}} \\
&= l_2^{(m)}(\omega_1 - \omega_2)\left(\frac{1}{l_1^{(m)} + l_2^{(m)}} - \frac{1}{l_1^{(w)} + l_2^{(m)}}\right) \\
&= l_2^{(m)}(\omega_1 - \omega_2)\frac{l_1^{(w)} - l_1^{(m)}}{(l_1^{(m)} + l_2^{(m)})(l_1^{(w)} + l_2^{(m)})}
\end{aligned}$$

Given that $l_1^{(w)}$ is a linear function of $l_1^{(m)}$, the wage gap is a function of $l_1^{(m)}$ and $l_2^{(m)}$, which we denote as $G(l_1^{(m)}, l_2^{(m)}; R)$.

Below, we show that G is a declining function of both $l_1^{(m)}$ and $l_2^{(m)}$. First, we analyze the relationship between G and $l_1^{(m)}$.

Substituting Equation (12) into the above expression, we have:

$$\bar{\omega}_w - \bar{\omega}_m = l_2^{(m)}(\omega_1 - \omega_2)\frac{\Delta c - \frac{a_w - a_m}{a_w} l_1^{(m)}}{(l_1^{(m)} + l_2^{(m)})(\frac{a_m}{a_w} l_1^{(m)} + \Delta c + l_2^{(m)})}$$

Following Lemma 2 and Assumption 1, we have:

$$\bar{\omega}_w - \bar{\omega}_m = (\omega_1 - \omega_2)\frac{\Delta c - \frac{a_w - a_m}{a_w} l_1^{(m)}}{(1 + \frac{l_1^{(m)}}{l_2^{(m)}})((\frac{a_m}{a_w} + A)l_1^{(m)} + \Delta c + B)}$$

Recall that $\omega_1 > \omega_2$ and $a_w - a_m > 0$. The numerator is a decreasing function of $l_1^{(m)}$, and thus an increasing function of R.

Under Assumption 1, both A and B take positive values, so $\frac{a_m}{a_w} + A)l_1^{(m)} + \Delta c + B)$ is an increasing function of $l_1^{(m)}$, so it is a decreasing function of R.

We are left with term $1 + \frac{l_1^{(m)}}{l_2^{(m)}}$. We show that it is also a decreasing function of R. From Lemma 2, $\frac{l_2^{(m)}}{l_1^{(m)}} = A + B/l_1^{(m)}$. Both A and B decreases with $l_2^{(m)}$, thus increasing with R. $B/l_1^{(m)}$ also increases with R. It is easy to see that $\frac{l_2^{(m)}}{l_1^{(m)}}$ increases with R, and therefore, $\frac{l_1^{(m)}}{l_2^{(m)}}$ decreases with R

Taken together, the racial wage gap $G = \bar{\omega}_w - \bar{\omega}_m$ is an increasing function of R. Put differently, when cost of financing declines, racial wage gap also decreases.

Q.E.D.

II Internet Appendix: Data Description

II.1 Longitudinal Employment-Household Dynamics (LEHD)

We use the employer-employee matched microdata maintained by the U.S. Census Bureau in their LEHD program to identify workers' races and track workers' earnings at their employers over time. The LEHD program is constructed from administrative unemployment insurance (UI) records of states participating in the program and contains every worker who has ever been employed in any participating state (see more details about the LEHD datasets in Abowd et al. (2009) and Vilhuber et al. (2018)). We have access to LEHD for 25 participating U.S. states from 1990 to 2014. Data coverage starts in 1990 for most states (except for Maryland, which starts in 1985), while other states' coverage begins later. Appendix Table IA.1 lists covered states and years available.

Within the covered states, the Employment History Files (EHF) of the LEHD program track workers' quarterly earnings, locations, and industries across employers. Workers' earnings include all forms of immediately taxable compensation, including gross wages and salaries, bonuses, exercised stock options, tips, and other gratuities.

Within the LEHD program, the National Individual Characteristics File (ICF) reports worker-level demographic characteristics and categorizes each worker into one of the following six racial groups: White, Black or African American, American Indian or Alaska Native, Asian, Native Hawaiian or Other Pacific Islander, or multi-race group.[1] If a person's race response is missing but at least one other member of the household reports a valid race, then the allocation is retained. However, this rule was not blindly applied. The quality of the allocation was confirmed using bestrace from the Numident. The correspondence with bestrace must be relatively high for the allocation to be retained. No hot (cold) deck allocations were retained (LEHD data manual, page 5-1 and 5-5).[2] We define all non-White workers as minority workers.

Besides race, ICF also reports workers' birth years, sex, and education levels. Demographic characteristics are imputed by the LEHD program using a hierarchical approach when missing. See more details about the imputation process in Section 5.1.1.2 of Vilhuber et al. (2018). Worker demographic characteristics from ICF can be linked to workers in EHF through the Census administrative worker identifiers.

To construct our baseline sample, we start with all workers between 18 and 64 years old observed in the accessible states. We retrieve these workers' entire work histories in the EHF and adjust earnings for inflation to 2018 Q3 constant dollars. While the EHF dataset allows us to observe quarterly earnings, it does not provide information on the number of weeks worked per quarter. The quarterly earnings may generate noise in our analysis if workers only worked part of the time within a quarter. Following conventions in the literature (Philippon and Reshef 2012; Ouimet and Zarutskie 2014; Babina 2019), we take the following three steps to eliminate those cases. First, we keep the observations with the highest earnings for each worker-quarter-year combination. Second, we drop observations with earnings below 50% of the federal minimum quarterly earnings.[3] Third, since worker transitions between jobs not occurring at the exact start of a new quarter would lead to a downward bias in earnings around a job change, we drop observations that do not have the same employee-employer pair in both the preceding and the subsequent quarter.[4] Lastly, to minimize the computational requirements of a large sample size, we reduce the data frequency from worker-quarter-year to worker-year by taking an average across quarterly earnings earned at each firm within a given year. If a worker worked at different firms within that year, we keep the job with the highest average earnings. From the LEHD data, we define our variable of interest *Log(Earnings)* as the natural logarithm of the average quarterly earnings a worker receives from a firm during a year.

[1]To collect race and ethnicity data, Federal agencies comply with the Statistical Policy Directive No. 15, which provides consistent race and ethnic data collection and reporting standards for Federal statistics and administrative reporting. See more details about the standards at `https://www2.census.gov/about/ombraceethnicityitwg/1978-statistical-policy-handbook.pdf`

[2]In Table 10, we observe consistent baseline results when excluding workers with imputed race.

[3]The federal minimum quarterly earning threshold=federal hourly minimum wage in a given year $\times$ 40 hours per day $\times$ 52 weeks /4 quarters. The U.S. federal minimum wage time series was downloaded from `https://www.dol.gov/agencies/whd/minimum-wage/history/chart`.

[4]A potential limitation of this adjustment is that we undersample workers who switch jobs twice in two subsequent quarters.

II.2 Longitudinal Business Database (LBD) and Compustat

Our analysis requires us to reliably identify the state of incorporation for firms. Information on incorporation states is available for publicly listed companies in Compustat. To this end, we first link worker-year data constructed from LEHD files with firm identifiers in the Census Bureau's LBD through the Business Register Bridge (BRB). The LBD tracks the universe of U.S. business establishments with at least one paid employee annually (see more details about LBD program in Jarmin and Miranda (2002) and Chow et al. (2021)). The longitudinal nature of the LBD allows us to define firm age using the oldest establishment with positive employment numbers that the firm owns in the first year the firm is observed in LBD (Haltiwanger et al., 2014). The full geographic coverage of the LBD allows us to measure firms' size by summing up their establishments' employment. Following the Statistics of U.S. Businesses program, we classify firms into 4-digit NAICS industries in which they paid the largest share of their payroll based on their establishment-level payroll data in LBD. We start our sample in 1990, which provides us with sufficient time series before the first adoption of the anti-recharacterization laws (1997). We end our sample in 2012 because the matching quality between LEHD and LBD worsens after 2012. We then link the LEHD-LBD matched sample with Compustat using the Compustat-SSEL Bridge (CSB) to obtain employers' gvkeys and their financial data. Lastly, for each gvkey-year, we merge in their historical incorporation states obtained from the SEC Analytics Suite by WRDS.[5]

II.3 Resume Data

We obtain proprietary resume data from Revelio Labs. Revelio gathers publicly available profiles from various sources and unifies employer names to create a unique set of company IDs. Their individual position data covers the names and unique identifiers of the employer, employee, job title, O*NET occupation codes, and estimated salary. Revelio imputes salary based on job title, company, location, years of experience, and seniority using a statistical model. Revelio provides each position's start and end dates. To correct potential lags in updating resumes, they also adopt a nowcasting model to provide a more timely estimate of the inflows and outflows of employees.

At the worker level, Revelio predicts the probabilities of a worker belonging to each racial group: White, Black, Asian and Pacific Islander, Hispanic, Native, or multiple races.[6] For a given worker, the sum of probabilities of belonging each group is equal to 100%. We define a worker as a minority if her probability of being a non-White worker exceeds 50%. Similarly, Revelio predicts a worker's sex using their first name. We also have information regarding their educational background from worker resumes.

In the resume data, the unit of observation is a worker's job span. From this dataset, we remove non-U.S. jobs and part-time jobs. We expand the remaining observations into a worker-year panel parallel to the one built from the Census data. A key procedure in constructing this sample is matching employers to Compustat's public firm identifier.[7] To do so, we start with the FactSet ID provided by Revelio, which links employer names to FactSet establishments. We then retrieve the historical corporate hierarchy from FactSet and connect them to the gvkey identifiers in Compustat back in time. This requires us to use linking tables that connect identifiers in FactSet to those in CRSP, and from CRSP to Compustat, both of which are provided by WRDS. This procedure provides us with a worker-firm-year panel, allowing us to track the progression of individual workers' career paths over time. After matching to public firms, our initial resume sample contains approximately 33 million unique workers and 70 million jobs.

We create several variables that indicate changes in workers' careers. First, we define *New Position* to be a binary variable that equals one if a worker is assigned to a different job position in the next year, and zero otherwise. This is an indicator of within-firm job mobility. Second, we define *Promotion* as an indicator for whether a worker changes his/her position and the new position offers a higher salary than the current one in the following year. Third, we define *Promotion Within Occ* as one if a worker changes to a higher-paying position within the same firm and the same three-digit SOC in the next

[5]We don't use the state of incorporation information in Compustat/CRSP because the incorporation sate may change over time, but the information provided in Compustat/CRSP only represents the most recent state of incorporation.

[6]The algorithm is a Bayesian Inference Model drawing data based on first and last names and locations. See more details about sex and racial group predictions at `https://www.data-dictionary.reveliolabs.com/methodology.html#gender-and-ethnicity`.

[7]While Revelio Labs provides a firm ID-gvkey mapping, the mapping is based on the most recent corporate structure and does not account for mergers and acquisitions over time.

year, and zero otherwise. Finally, we code *Change to Tech-oriented* as an indicator for whether a worker changes their job code from a non-tech-oriented category to a tech-oriented category within a firm. The classification of tech-oriented occupations follows Hecker (2005) and refers to scientific, engineering, and technician occupations, which include the following occupational groups and detailed occupations: computer and mathematical scientists, Standard Occupational Classification (SOC) 15-0000; engineers, SOC 17–2000; drafters, engineering, and mapping technicians, SOC 17–3000; life scientists, SOC 19–1000; physical scientists, SOC 19–2000; life, physical, and social science technicians, SOC 19–4000; computer and information systems managers, SOC 11–3020; engineering managers, SOC 11–9040; and natural sciences managers, SOC 11–9120. Workers in these occupations need an in-depth knowledge of the theories and principles of science, engineering, and mathematics underlying technology, a knowledge generally acquired through specialized post-high school education in some field of technology leading up to an award ranging from a vocational certificate or an associate's degree to a doctorate. Individuals employed in these occupations are collectively referred to as technology-oriented workers. All indicators are multiplied by 100, so our coefficients indicate job transition and promotion rates in percentage points.

Table IA.1
LEHD Sample Coverage
This table presents the accessible states and years in the Employment History File (EHF) maintained by the U.S. Census LEHD program. See Vilhuber et al. (2018) for details of the LEHD program.

State	First year	Last year
Arkansas	2002	2014
Arizona	1992	2014
California	1991	2014
Colorado	1990	2014
D.C.	2002	2014
Delaware	1998	2014
Hawaii	1995	2014
Idaho	1990	2014
Illinois	1990	2014
Indiana	1990	2014
Iowa	1998	2014
Kansas	1990	2014
Maine	1996	2014
Maryland	1985	2014
Missouri	1994	2014
Nevada	1998	2014
New Mexico	1995	2014
New York	1995	2014
North Dakota	1998	2014
Ohio	2000	2014
Oklahoma	2000	2014
Pennsylvania	1991	2014
Tennessee	1998	2014
Virginia	1998	2014