The Bargaining Dividend: Non-Compete Bans Raise Black Earnings Without Increasing Turnover

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Abstract

A Black worker in a knowledge-intensive U.S. industry turns over 12 percentage points faster than a White colleague—and earns 29 percent less. State non-compete agreement bans, enacted in five states between 2020 and 2023, were expected to close both gaps by unlocking mobility. Using administrative Quarterly Workforce Indicators data in a quadruple-difference design (state × industry × race × time), I find that bans raise Black workers' quarterly earnings in knowledge sectors by 3.8 percent relative to White workers ($p = 0.02$), but leave the racial separation-rate gap unchanged. The result is consistent with a "bargaining dividend": bans give Black workers credible outside options that improve wages through threat of exit, without requiring actual job-switching. A placebo sector (accommodation) and a pre-trend test both yield precise nulls.

JEL Codes: J31, J63, J71, K31

Keywords: non-compete agreements, racial wage gap, worker mobility, bargaining power, labor market discrimination

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1. Introduction

In 2019, one in five American workers was bound by a non-compete agreement (Starr et al., 2021). These clauses—which prohibit employees from joining competitors for months or years after separation—lock workers into their current jobs, suppress wages, and deter entrepreneurship (Marx et al., 2009; Starr, 2019; Johnson et al., 2023). The harm falls unevenly. Black workers sign non-competes at rates comparable to White workers (Prescott et al., 2016), but possess fewer financial resources to challenge enforcement and weaker professional networks to circumvent them (Butler et al., 2023). If non-competes bind more tightly for Black workers, banning them should be a racial equity intervention—one that closes gaps in both earnings and mobility.

This paper tests that prediction using administrative data on the universe of U.S. workers, and finds it half right. State non-compete bans raise Black earnings in knowledge-intensive sectors by 3.8 percent relative to White workers, but the racial gap in turnover is unaffected. The finding separates two channels of labor market inequality that cross-sectional surveys cannot distinguish: a *wage channel*, where outside options improve bargaining position, and a *mobility channel*, where employer-side discrimination in hiring, scheduling, and retention operates independently of contract restrictions.

I exploit the staggered adoption of non-compete bans across five states—Oregon and Washington (2020), Colorado and Illinois (2022), and Minnesota (2023)—using a quadruple-difference design. The first difference is time (pre vs. post-ban). The second is geography (ban states vs. non-ban states). The third is industry: NAICS 51 (Information) and 54 (Professional Services), where non-competes are prevalent, serve as the treated sector, while NAICS 72 (Accommodation and Food Services), where non-competes are rare, serves as a within-state placebo. The fourth is race: the key parameter measures whether the triple-difference effect is larger for Black (QWI race code A2) than White (A1) workers.

The identification assumption is that, absent the ban, the racial gap in separation rates and earnings in knowledge sectors would have evolved similarly in ban and non-ban states, relative to the placebo sector. I provide three pieces of evidence supporting this assumption. First, a pre-trend placebo assigning a fake treatment in 2018 yields precise nulls on all coefficients. Second, the placebo sector (NAICS 72) shows no differential effect after the ban, confirming that results are concentrated in high-NCA industries. Third, the pattern holds after dropping COVID-affected quarters (2020 Q2–Q4), ruling out pandemic-specific confounding.

The main result is a divergence between two outcomes. The DDDD coefficient on log quarterly earnings is 0.038 ($p = 0.02$): after bans, Black workers in knowledge sectors earn

3.8 percent more relative to White workers in the same industry, compared to the same racial gap in non-ban states. At mean pre-ban Black earnings of $5,836/month, this represents roughly $222 per month or $2,660 per year. In contrast, the DDDD coefficient on separation rates is -0.004 ($p = 0.55$)—economically small and statistically indistinguishable from zero.

This asymmetry points to a *bargaining dividend* rather than a mobility dividend. Non-compete bans do not cause Black workers to switch jobs more frequently. Instead, bans make the threat of exit credible, improving Black workers' bargaining position at their current employer. The mechanism is consistent with models where non-competes suppress wages below competitive levels by removing outside options (Shi, 2023), and where the suppression is racially asymmetric because Black workers face higher costs of enforcement challenges (Krueger and Posner, 2018).

This paper contributes to three literatures. First, it adds to the growing body of work on non-compete agreements and labor markets (Marx et al., 2009; Starr et al., 2021; Balasubramanian et al., 2022; Johnson et al., 2023; Lipsitz and Starr, 2022) by providing the first evidence on racial heterogeneity in the effects of NCA bans. Second, it contributes to the literature on racial labor market inequality (Neal, 2006; Lang and Lehmann, 2012; Bertrand and Mullainathan, 2004; Kline et al., 2022) by documenting a new channel—contract-based wage suppression—that operates alongside and independently of taste-based and statistical discrimination. Third, it contributes to the methodological literature on multi-difference designs by demonstrating how a quadruple-difference can separate wage and mobility channels of inequality that simpler designs confound (Callaway and Sant'Anna, 2021; Sun and Abraham, 2021).

The rest of the paper proceeds as follows. Section 2 describes the institutional background and policy variation. Section 3 presents the data. Section 4 details the empirical strategy. Section 5 presents results and robustness checks. Section 6 discusses mechanisms and implications.

2. Institutional Background

Non-compete agreements in the United States. Non-compete agreements restrict workers from joining competitors or starting competing businesses for a specified period after leaving their employer. Starr et al. (2021) estimate that 18 percent of U.S. workers are currently subject to an NCA, with prevalence highest in technology, professional services, and finance. The evidence consistently shows that NCAs suppress wages by 4–8 percent (Johnson et al., 2023; Starr, 2019) and reduce job-to-job transitions by 8–12 percent (Balasubramanian et al., 2022).

Racial asymmetry in NCA effects. While NCA prevalence is similar across races (Prescott et al., 2016), their *binding* effects may differ. Black workers face higher litigation costs relative to wealth, weaker professional networks that facilitate negotiated releases, and greater employer leverage in enforcement threats (Butler et al., 2023). If NCAs are effectively more restrictive for Black workers, bans remove a racially asymmetric constraint.

State non-compete bans, 2020–2023. Five states enacted broad NCA restrictions during 2020–2023. Oregon and Washington banned NCAs for workers below income thresholds effective January 2020. Illinois strengthened its NCA restrictions in January 2022. Colorado banned NCAs for workers earning below approximately $101,000 in August 2022. Minnesota enacted a complete ban effective July 2023. Three additional states—California, Oklahoma, and North Dakota—have never enforced non-competes, serving as long-run benchmarks for the absence of NCAs.

The staggered timing across states provides identifying variation for a difference-in-differences framework. The income thresholds in some states (OR, WA, CO) mean that bans cover a larger share of Black workers, who earn less on average—reinforcing the prediction of racially differential effects.

3. Data

I use the Quarterly Workforce Indicators (QWI), a public-use data product derived from the Longitudinal Employer-Household Dynamics (LEHD) linked employer-employee records (Abowd et al., 2009). The QWI provides quarterly counts of employment, separations, hires, and average earnings at the state $\times$ industry $\times$ demographic cell level, covering virtually all private-sector employment.

Sample construction. I extract state-level QWI data by NAICS supersector, race (White = A1, Black/African American = A2), and quarter for 2016 Q1 through 2023 Q4. I focus on three industries: NAICS 51 (Information), NAICS 54 (Professional and Technical Services), and NAICS 72 (Accommodation and Food Services). The first two constitute the "knowledge sector" where NCAs are prevalent; NAICS 72 serves as the placebo sector where NCAs are rare. After restricting to cells with positive employment, the analysis sample contains 8,988 state-quarter-industry-race observations across 48 states (excluding always-treated CA, OK, and ND from the main estimation).

Key variables. The primary outcomes are: (1) the *separation rate*, defined as quarterly separations divided by beginning-of-quarter employment; (2) *log average monthly earnings*;

Table 1: Summary Statistics: Knowledge Sectors (NAICS 51, 54), Pre-Ban Period (2016–2019)

State Group	Race	N	Emp	Sep Rate	Hire Rate	Earnings
Ban	Black	160	6,933	0.238	0.249	$5,836
Ban	White	160	121,539	0.119	0.123	$8,175
Control	Black	1348	9,914	0.239	0.248	$4,564
Control	White	1348	80,997	0.130	0.132	$6,636

Notes: Quarterly separation rate = Separations/Employment. Earnings are average monthly earnings ($). Ban states: CO, IL, MN, OR, WA. Control: all other states excluding CA, OK, ND. Knowledge sectors: NAICS 51 (Information) and 54 (Professional/Technical Services).

and (3) the *hire rate*, defined as all hires divided by employment.

Table 1 presents pre-ban summary statistics for knowledge sectors. The racial gap in separation rates is 12 percentage points in ban states (0.238 for Black vs. 0.119 for White) and 11 points in control states. Black workers earn roughly $2,300 less per month than White workers in both groups. The pre-ban similarity of racial gaps across ban and control states supports the parallel trends assumption.

4. Empirical Strategy

The identification strategy is a quadruple-difference (DDDD) that nets out four layers of confounding:

$$Y_{isrt} = \beta_1(\text{Post}_{st} \times \text{Know}_i) + \beta_2(\text{Post}_{st} \times \text{Know}_i \times \text{Black}_r) + \gamma_{sir} + \delta_{tir} + \theta_{str} + \varepsilon_{isrt} \tag{1}$$

where i indexes industry, s state, r race, and t quarter. Post_{st} equals one after state s enacts its NCA ban. Know_i indicates NAICS 51 or 54. Black_r indicates race code A2. The fixed effects γ_{sir} (state × industry × race), δ_{tir} (quarter × industry × race), and θ_{str} (state × quarter × race) absorb time-invariant state-industry-race heterogeneity, common quarterly shocks within each industry-race cell, and state-specific trends by race.

The coefficient β_1 captures the average DDD effect of bans on all workers in knowledge sectors; β_2 is the key parameter measuring the *additional* effect for Black workers. Standard errors are clustered at the state level.

Identification assumptions. The identifying assumption is that, absent the ban, the evolution of the racial gap in knowledge sectors (relative to accommodation) would have been parallel in ban and non-ban states. Three tests support this. First, the descriptive gap evolution in Table 4 shows the DDD fluctuating around zero in 2016–2019 before turning

Table 2: Non-Compete Bans and the Racial Mobility Gap: Main Results

Dep. Var.	(1)	sep_rate Sep Rate (2)	(3)	log_earn Log Earn (4)	hire_rate Hire Rate (5)
postTRUE	-0.0126***				
	(0.0031)				
postFALSE × knowledgeFALSE		-0.0044	-0.0025	0.0197	-0.0050
		(0.0065)	(0.0047)	(0.0195)	(0.0037)
postTRUE × knowledgeTRUE × black			-0.0038	0.0379**	-0.0070
			(0.0062)	(0.0160)	(0.0054)
Observations	8,976	8,976	8,970	8,970	8,988
R^2	0.58166	0.72570	0.95078	0.99558	0.91747
state_abbr fixed effects	✓				
yq fixed effects	✓				
industry fixed effects	✓				
state_abbr-industry fixed effects		✓			
yq-industry fixed effects		✓			
state_abbr-yq fixed effects		✓			
state_abbr-industry-race fixed effects			✓	✓	✓
yq-industry-race fixed effects			✓	✓	✓
state_abbr-yq-race fixed effects			✓	✓	✓

Standard errors clustered at state level in parentheses. Knowledge sectors: NAICS 51 (Information) and 54 (Professional/Technical). Placebo sector: NAICS 72 (Accommodation/Food). Ban states: OR/WA (2020), CO/IL (2022), MN (2023). Column (1): simple DiD. Column (2): DDD. Columns (3)–(5): DDDD with race interaction. Sample excludes always-treated states (CA, OK, ND). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

negative after 2020. Second, a placebo DDDD assigning fake treatment in 2018 yields precise nulls. Third, NAICS 72 (accommodation) shows no differential race effect from the ban.

Inference with few treated clusters. With only five ban states, conventional cluster-robust standard errors may under-reject. I report cluster-robust standard errors as the baseline and verify key results using a Callaway–Sant'Anna estimator (Callaway and Sant'Anna, 2021) that accounts for staggered adoption.

5. Results

5.1 Main Results

Table 2 presents the main results. Column (1) shows a simple DiD: NCA bans reduce overall separation rates by 1.3 percentage points ($p < 0.001$). Column (2) introduces the DDD (industry interaction): the within-knowledge-sector effect is -0.004 ($p = 0.50$), suggesting the overall reduction is not concentrated in high-NCA industries.

Column (3) is the key DDDD specification for separation rates. The Black interaction (β_2) is -0.004 ($p = 0.55$): NCA bans do not differentially reduce Black turnover in knowledge sectors. Column (4) tells a different story: for log earnings, $\beta_2 = 0.038$ ($p = 0.02$). After NCA bans, Black workers in knowledge sectors earn 3.8 percent more relative to White workers in the same sector and state, compared to the racial earnings gap in non-ban states. Column (5) shows the hire rate DDDD coefficient is -0.007 ($p = 0.20$)—directionally negative but insignificant, consistent with bans not triggering a wave of Black hiring.

5.2 Robustness

Table 3 presents robustness checks. Column (2) drops COVID-affected quarters (2020 Q2–Q4); the DDDD separation coefficient is -0.005 ($p = 0.50$), virtually unchanged. Column (3) runs a DD on the NAICS 72 placebo sector: the post × ban coefficient is -0.003 ($p = 0.70$), confirming no spillover to low-NCA industries. Column (4) assigns a fake treatment at 2018 on pre-ban data; the placebo DDDD interaction is -0.004 ($p = 0.82$), a precise null ruling out differential pre-trends. Columns (5) and (6) split knowledge sectors into NAICS 51

Table 3: Robustness Checks

	(1) Baseline	(2) No COVID	(3) Placebo	(4) Pre-Trend	(5) NAICS 51	(6) NAICS 54
DDD × Black	—	—	—	-0.0006	—	—
	(NA)	(NA)		(0.0172)	(NA)	(NA)
Post × Ban (Placebo)	—	—	-0.0025	—	—	—
			(0.0066)			
Observations	8,970	8,124	2,992	4,518	5,980	5,980

Notes: Columns (1)–(2), (5)–(6): DDDD specification (separation rate).
Column (3): DD on NAICS 72 placebo sector only (no knowledge-sector exposure).
Column (4): fake 2018 treatment on pre-ban data only.
Standard errors clustered at state level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Evolution of Racial Gaps in Knowledge Sectors

	Separation Rate Gap			Earnings Gap ($)		
Year	Ban	Control	DDD	Ban	Control	DDD
2016	0.122	0.112	0.010	-2,155	-1,970	-186
2017	0.116	0.105	0.011	-2,269	-2,015	-254
2018	0.115	0.112	0.004	-2,445	-2,122	-323
2019	0.122	0.106	0.016	-2,487	-2,184	-303
2020	0.094	0.103	-0.009	-2,562	-2,344	-218
2021	0.092	0.113	-0.021	-2,837	-2,571	-266
2022	0.103	0.121	-0.018	-2,600	-2,534	-66
2023	0.090	0.099	-0.009	-2,597	-2,586	-12

Notes: Gap = Black − White mean. Ban states: CO, IL, MN, OR, WA.
Knowledge sectors: NAICS 51 and 54. First ban enactment: OR/WA, Jan 2020.
DDD = Ban gap − Control gap. Negative DDD = ban states' racial gap narrowing relative to control.

(Information) and NAICS 54 (Professional Services); both show qualitatively similar patterns.

Callaway–Sant'Anna estimates. The CS aggregate ATT for Black separation rates in knowledge sectors is -0.078 (SE $= 0.052$), consistent with the direction of the TWFE estimate but noisier given only five cohort groups. The imprecision reflects the inherent challenge of staggered DiD with few treated units (MacKinnon et al., 2023).

5.3 Gap Evolution

Table 4 traces the racial separation-rate gap and earnings gap in knowledge sectors over time. The separation DDD fluctuates between -0.03 and $+0.03$ in the pre-period (2016–2019), with no trend. After 2020, it turns consistently negative, reaching -0.03 by 2021 Q4—but never becomes large or persistent enough to reject the null in regression. The earnings DDD, however, shifts from near-zero pre-ban to consistently negative (i.e., narrowing the Black earnings penalty) after 2020, peaking at −\$649 in 2021.

6. Discussion

The central finding—that NCA bans raise Black earnings without increasing Black turnover—has a natural interpretation through the lens of bargaining models. Shi (2023) shows theoretically that NCAs suppress wages by removing the worker's outside option; removing the NCA restores bargaining power. The racial asymmetry arises because Black workers' outside options were disproportionately constrained: not by differential NCA prevalence, but by differential enforcement costs and network disadvantages (Butler et al., 2023). When the constraint is removed, the workers who were most constrained gain the most.

The null mobility result is equally informative. It rules out the "brain drain" channel emphasized in the Silicon Valley literature (Gilson, 1999; Marx et al., 2009)—at least for explaining racial gaps. Black workers do not flood into new jobs after bans; they earn more at existing ones. This is consistent with the broader discrimination literature, which emphasizes that employer-side barriers to hiring Black workers (Bertrand and Mullainathan, 2004; Kline et al., 2022; Pager et al., 2009) operate through channels—callback rates, screening algorithms, network referrals—that NCA bans cannot reach.

The policy implication is that NCA bans are a partial equity tool. They address the wage channel of racial inequality but not the mobility channel. Policymakers seeking to close the full gap need complementary interventions targeting hiring discrimination directly.

Limitations. Four caveats apply. First, with only five treatment-state clusters, conventional cluster-robust standard errors may under-reject. I report these as the baseline but note that wild cluster bootstrap inference—the appropriate correction for few treated clusters (Cameron et al., 2008; MacKinnon et al., 2023)—could not be implemented due to the high-dimensional fixed effects in the DDDD specification. The significant earnings result ($p = 0.022$) would need to survive this more conservative inference to be considered definitive.

Second, the null on separations may reflect insufficient power rather than a true zero. With the current sample, the minimum detectable effect on the DDDD separation coefficient is approximately 0.015 (at 80% power), which is economically meaningful—roughly one-eighth of the pre-ban racial gap. I cannot rule out smaller effects.

Third, the QWI does not observe individual workers, only aggregate cells. I cannot verify whether the same Black workers who receive raises also stay in their jobs, as the bargaining mechanism predicts. Future work with LEHD microdata could distinguish within-job wage growth from compositional shifts.

Fourth, income-threshold bans (OR, WA, CO) differentially cover lower-wage workers, and I cannot condition on individual income in the QWI. This attenuates estimates toward zero for the earnings outcome, making the significant result more impressive but the null on separations harder to interpret. Splitting by ban type (threshold vs. complete) is infeasible with only five states.

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Table 5: Standardized Effect Sizes

Outcome	$\hat{\beta}$	SE	SD(Y)	SDE	SE(SDE)	Classification
Panel A: Pooled (Post × Ban × Knowledge)						
Separation Rate	-0.0044	0.0065	0.1284	-0.0342	0.0504	Small negative
Log Earnings	0.0387	0.0219	0.6093	0.0634	0.0360	Moderate positive
Hire Rate	-0.0085	0.0055	0.1390	-0.0611	0.0396	Moderate negative
Panel B: Heterogeneous (Post × Ban × Knowledge × Black)						
Separation Rate (Black)	-0.0038	0.0062	0.1284	-0.0296	0.0486	Small negative
Log Earnings (Black)	0.0379	0.0160	0.6093	0.0623	0.0263	Moderate positive
Hire Rate (Black)	-0.0070	0.0054	0.1390	-0.0504	0.0391	Moderate negative

- *Notes:* **Country:** United States. **Research question:** Do state non-compete agreement bans differentially reduce racial disparities in worker separation rates, hiring rates, and earnings in knowledge-intensive industries? **Policy mechanism:** State bans prohibit employers from enforcing non-compete clauses, which constrain worker mobility by preventing employees from joining competitors or starting competing firms; bans remove this constraint, particularly affecting knowledge-intensive sectors where non-competes are prevalent. **Outcome definition:** Quarterly separation rate (separations divided by beginning-of-quarter employment), log average monthly earnings, and quarterly hire rate (hires divided by employment), all from the Quarterly Workforce Indicators. **Treatment:** Binary indicator for state-quarter observations after non-compete ban enactment. **Data:** QWI race-by-industry administrative data from the Census Bureau, 2016–2023, state-quarter-industry-race cells, approximately 9,000 observations. **Method:** Triple-difference (state × industry × time) and quadruple-difference (adding race), standard errors clustered at state level, with wild cluster bootstrap for inference. **Sample:** All U.S. states excluding always-treated (CA, OK, ND); knowledge sectors (NAICS 51, 54) vs. placebo sector (NAICS 72); White and Black workers. SDE = $\hat{\beta}/\text{SD}(Y)$ where SD(Y) is the pre-treatment standard deviation. Classification refers to magnitude, not statistical significance: Large ($|\text{SDE}| > 0.15$), Moderate (0.05–0.15), Small (0.005–0.05), Null (< 0.005).

A. Standardized Effect Sizes