Outside the Box: Measuring the Unintended Consequences of Ban the Box Policies at an Industry Level

UNC KENAN-FLAGLER BUSINESS SCHOOL

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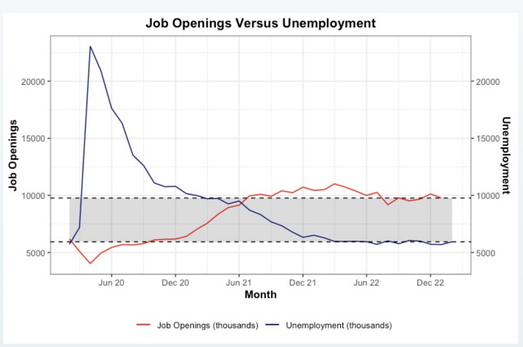
Abstract

As firms continue struggling through the contemporary labor shortage, traditionally overlooked populations present an opportunity to expand the workforce. Ban the box (BTB) policies have emerged as a popular mechanism to improve ex-offender hiring, in particular, by prohibiting criminal background inquiries on job applications. However, recent research suggests BTB may unintentionally worsen overall employment outcomes for Black and Hispanic men by inviting statistical discrimination. This thesis investigates how BTB-induced discrimination varies across industries. Using the Callaway and Sant'Anna difference estimator, I estimate BTB's effect on Black and Hispanic shares of hires across nine industries. Overall, BTB improved Black and Hispanic hiring in most industries, though the effect on Black shares often diminished over time. Reductions in hire shares were rare and only observed in customer-facing industries with low entry barriers. This study highlights the importance of considering industry-specific consequences when creating policies to improve ex-offender employment outcomes.

Introduction

Despite some recovery from pandemic-induced labor shocks, civilian employment and labor force participation still lag considerably behind pre-COVID growth trends. According to the Bureau of Labor Statistics (2023), current employment falls 5 million short of projections based on pre-pandemic observations. Reduced workforce participation and availability also create difficulties for firms as they seek to fill necessary roles: job openings currently exceed the number of unemployed Americans by over 4 million (see below).



Firms struggle to fill open positions, yet numerous studies have found that firms may counterintuitively exclude eligible workers from consideration. **Ex-offenders**, or individuals with criminal histories, are routinely disqualified from work opportunities, which costs the U.S. economy millions of available workers and billions of dollars in productivity (Schmitt & Warner, 2008).

Ban the box (BTB) policies seek to increase the number of ex-offenders in the workforce by precluding inquiries about criminal histories on job applications. While most policies still allow eventual background checks, BTB proponents argue that the policy will improve ex-offender hiring outcomes by providing more interview and rapport building opportunities before an applicant is labeled by their criminal background.

However, recent studies have found that BTB may unintentionally spur hiring discrimination against Black and Hispanic applicants, especially men (Agan & Starr, 2018; Doleac & Hansen, 2020). The literature suggests that BTB invites **statistical discrimination** against these groups: firms use disproportionately high incarceration rates among Black and Hispanic men as a proxy for actual criminal history.

These studies did not distinguish how discriminatory effects vary by industry, however. Given evidence that second chance hiring aversion differs between industries, this honors thesis investigated how BTB affects overall Black and Hispanic hire shares across 9 disparate industries.

Methodology

Industry Selection

I selected **9 different industries**, comprising **2 different industry pools**, to measure how BTB-induced hiring discrimination varies in different employment sectors. The first industry pool, which I refer to as the high propensity pool, consisted of industries that ex-offenders enter at the highest rate. The low propensity pool, in contrast, consisted of industries with some aversion to hiring ex-offenders. Little data exists on which industries hire ex-offenders least often, so I instead used characteristics like customer interaction and money handling to approximate aversion.

	Industry	NAICS Code
High Propensity Industry Pool	Administrative Services	56
	Food Services	72
	Construction	23
	Retail Trade	44-45
	Manufacturing	31-33
Low Propensity Industry Pool	Management	55
	Health Care	62
	Education	61
	Finance	52

Dependent Variables

I measured BTB's effect on **three dependent variables**, included in the table below. I only considered new hires (i.e. no recall hires) because BTB should intuitively only invite discrimination against candidates that employers have no prior relationship with.

Dependent Variable	Formula	Data Source
Black Hire Share (B)	$\frac{New\ Black\ Hires}{Total\ New\ Hires}$	QWI
Hispanic Hire Share (H)	$\frac{New\ Hispanic\ Hires}{Total\ New\ Hires}$	
Black and Hispanic Combined Hire Share (BH)	$\frac{New\ Black\ Hires + New\ Hispanic\ Hires}{Total\ New\ Hires}$	

Treatment Effect Estimator

Research estimating policy treatment effects traditionally employs a **difference-in-differences (DD)** regression model, but new studies have uncovered severe flaws with DD when using two-way fixed effects (TWFE) to control for unit and time variation (Callaway & Sant'Anna, 2021; Goodman-Bacon, 2021). When dealing with multiple treatment periods, TWFE violates the parallel trends assumption by assigning a pre-treated unit to the control group when assessing effects on later-treated groups. This error can produce inaccurate or even wrong-sign results, especially when treatment effects are dynamic (Callaway & Sant'Anna, 2021).

To calculate more accurate and reliable results, I used the **Callaway and Sant'Anna (CS) difference estimator**, which was designed specifically to calculate treatment effects with multiple treatment periods. CS calculates the average treatment effect (ATT) for each group-time observation. That is, it calculates an estimate for each treatment group—counties that received treatment in the same quarter—in every quarter.

Because individual group-time ATTs do not provide insight into BTB's overall effects on hiring discrimination, I applied two levels of aggregation. **Group-aggregated Overall ATT** calculates BTB's overall effect and **dynamic-aggregated ATTs** depict how treatment effects changed based on length of exposure.

$$ATT_{(g,t)}$$

1 **Group Aggregation**
Weighted average by treatment group
Calculates Overall ATT

2 **Dynamic (Event Study) Aggregation**
Weighted average by length of exposure
Depicts changes in ATT over time

Finding 1: Positive Industry Pool Coefficients

The table below shows that the ban the box's Overall ATT, or treatment effect, was positive for nearly every dependent variable in both industry pools. While I found some variation at the industry level, the positive effect on both pools indicates that **BTB broadly increased the Black and Hispanic share of hires.** This suggests that BTB does not incite widespread statistical discrimination, as other researchers have found.

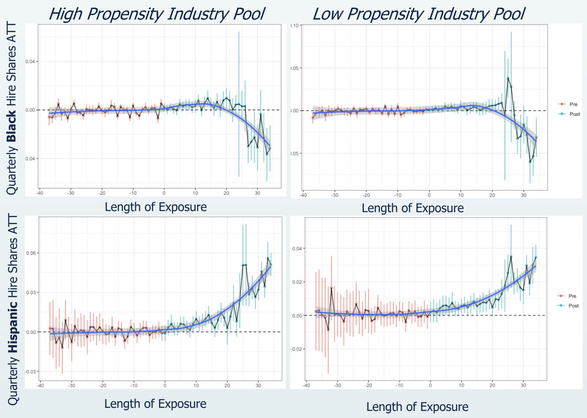
Dependent Variable	High Propensity	Low Propensity
Black *(B)*	0.0038*** (0.0008)	0.0031*** (0.0009)
Hispanic *(H)*	0.0039** (0.0015)	0.0038** (0.0019)
Black and Hispanic *(BH)*	0.0021 (0.0019)	0.0055** (0.0023)

Standard errors are located beneath each coefficient in parentheses
$^{**}p \leq 0.05$. $^{***}p \leq 0.01$

However, I do not contend that BTB directly incentivizes diverse hiring practices. The policy's focus on helping exclusively ex-offenders warrants skepticism that it somehow promotes diverse hiring. A more feasible interpretation is that BTB improved ex-offender hire rates where I witness positive results, which mathematically increased Black and Hispanic hire shares.

Finding 2: Black and Hispanic Dynamic Trends

Despite calculating positive Overall ATTs using group-aggregated estimates, dynamic estimates add more nuance to BTB's effect on Black and Hispanic hiring. The event study plots below illustrate how the effect changed based on the number of quarters before or after implementation. As illustrated, **the effect on Black hire shares trended negatively in both industry pools, while the positive effect on Hispanic hiring increased over time.**



Although, the event study plots should be interpreted cautiously. As shown, the standard error bars are very large beyond around 25 quarters, likely because the number of observations at those exposure lengths is extremely limited. Results are hardly generalizable beyond 30 quarters especially because only Philadelphia County implemented BTB early enough to record observations 30 quarters after implementation. Regardless, the difference in trend direction is noteworthy, as it is seen in both pools and numerous industries.

Literature points to two primary explanations for the trend differences:

1. If statistical discrimination does play some role, Black applicants should experience a more negative effect than Hispanic applicants, given higher incarceration rates among the Black community.
2. Doleac and Hansen (2020) found that Hispanic outcomes appear more resilient than Black outcomes in the face of discrimination because Hispanic communities are more likely to rely on their social networks to find employment.

Finding 3: Industry-Specific Positive Effect Drivers

While this does not account for every single positive effect I calculated, I observed that **BTB primarily increased Black and Hispanic hire shares in industries that offer high wages while still being reasonably accessible to ex-offenders.** Wages are high in construction, manufacturing, and all low propensity industries. All high propensity industries are accessible to ex-offenders, but I also considered Health Care and Social Services (NAICS 62) reasonably accessible because between 3-5% of ex-offenders find work in the sector within 4 years post-release.

Blue rows in the table below depict the high wage and reasonable accessibility industries. Effects were positive in each of these industries for at least one dependent variable. Consistent with my interpretation of overall positive effects, I infer that these results stem from an increase in ex-offender hiring.

Finding 4: Industry-Specific Negative Effect Drivers

Negative effects were concentrated only in industries with high levels of customer interaction and low entry barriers, which is consistent with the literature. Ex-offender aversion is highest in industries where employees deal with customers frequently because employers often view them as untrustworthy liabilities.

Industries with high entry barriers likely still maintain the same level of offender aversion, but they can use more reliable applicant characteristics like education and work histories to vet out those with criminal histories.

The red rows in the table below highlight industries with high customer interaction and low barriers. Note that, while the effect is insignificant in administrative services at the full covariate control level, I observed negative effects before controlling for economic activity. Additionally, the Overall ATT in food services is positive, which casts doubt on my inference. Although, the positive effect could be driven by back-of-house kitchen hires, which are often not customer-facing.

Industry	Dependent Variable: *B*	*H*	*BH*
Administrative Services	-	-	-
Food Services	0.0077***	-	0.0052*
Construction	-	0.0072*	-
Retail Trade	-	-	-0.0071**
Manufacturing	-	0.0128***	0.0132***
Management	-	-	0.0096**
Health Care	0.0081***	0.0050*	0.0098**
Education	0.0032*	-	-
Finance	-	-	-

Values are only reported for significant treatment effect estimates.
$^{*}p \leq 0.10$. $^{**}p \leq 0.05$. $^{***}p \leq 0.01$

Recommendations for Future Research

1. Measure the effect on more specific demographic groups: low-skilled Black and Hispanic men. Due to data limitations, my analysis only measures the effect on overall Black and Hispanic hiring.
2. Use finer industry or occupation-level data to capture additional variation.
3. Collect data over a longer post-implementation period to fully capture dynamic effects in the Overall ATT calculation
4. Include additional covariate controls and conduct separate analyses by geographic region to better account for endogeneity
5. Consider conducting research on wrap-around ecosystem approaches that help facilitate all facets of ex-offender re-entry

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