General Employment Effects of Ban-the-Box and Certificate of Restoration Policies

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This paper represents my own work in accordance with University regulations

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I. Introduction

The proliferation of the incarcerated population in the late 1900s and early 2000s has resulted in a large-scale loss of economic opportunities for incarcerated people, as the label "felon" follows ex-offenders throughout their employment search process after release. In 2020, over 608,000 sentenced inmates were released from state and federal correctional institutions (Carson, 2020). In the nine years following release, five in six state inmates released in 2005 were arrested at least once, and in the three years following release, two-thirds were arrested for a new crime (Alper et al., 2018). Research has shown that ex-offenders who are able to find employment after release are much less likely to recidivate, meaning that they have a decreased probability of engagement in criminal activity again (Holzer et al., 2003; Yang, 2017). As crime is costly, both in terms of psychological and financial damage, reducing recidivism is key to improving the overall wellbeing of society. Thus, increasing employment opportunities for qualified ex-offenders produces social, economic, and individual benefit by reducing future crime, decreasing costs of crime, and providing meaningful employment.

This paper will focus on the effects of recent employment policies designed to benefit ex-offenders. Specifically, it examines general employment effects among populations similar in demographic to ex-offenders, focusing on recent Ban-the-Box (BTB) laws and Certificate of Rehabilitation (COR) policies. Both of these policies aim to provide relief by lowering barriers for ex-offenders in reentering the workforce but differ in their approaches and mechanisms. Ban-the-Box laws work through the employer-side by restricting information on whether an applicant has a criminal record, and Certificates of Rehabilitation are awarded to ex-offenders by judicial courts, deeming them rehabilitated for employment.

The analysis will be conducted through a series of event studies and difference-in-difference analyses, specifically focusing on low-skilled, young adults. First, using data drawn from the Current Population Survey, I leverage the variation in timing of BTB policies across states to test effects on employment outcomes. By tracking the evolution of employment outcomes prior to and subsequent to implementation of a BTB policy, I am able to examine effects of the policy over time. This analysis will be conducted over several periods, spanning a total of 54 months for each policy implementation date. Second, I will conduct a difference-in-differences study to examine employment effects of the COR policy. Similar to the first analysis, the time period of interest spans 54 months, from September 2010 to March 2015. The treatment group, Ohio, implemented a COR-equivalent policy in September 2012, called the Certificate of Qualification for Employment. The treatment group is compared to Michigan, the control group, which is demographically similar to Ohio. The difference-in-difference analysis relies on two assumptions, that trends in the treatment and control groups are similar prior to the policy date and that there was no substantial anticipation of the policy. Finally, I conduct a preliminary analysis on the joint effect of BTB laws and COR policies by examining employment effects following implementation a BTB policy in Ohio, as the BTB law came into effect while the CQE policy was already in place. This analysis compares employment trends for young, low-skilled Blacks in Ohio to the state average and to the average effect across BTB states.

This study finds that BTB laws have had, at most, negligible effects on employment outcomes for young, low-skilled Black males and females. It also demonstrates that in the face of BTB adoption, employers do not appear to substitute towards Hispanic individuals of similar backgrounds. Previous literature has demonstrated that BTB laws have unintended consequences due to increased statistical discrimination, as detailed later in this paper. The findings in this paper are consistent with previous literature by reinforcing the non-beneficial effects of BTB policies. Additionally, this paper adds to growing literature on COR policies, finding that there are not statistically significant effects of the policy on young, low-skilled individuals; however, preliminary analyses demonstrate that the preexisting CQE policy in Ohio may have led to counteracting effects to the subsequently adopted BTB policy. Two mechanisms are proposed to explain these effects.

The remainder of this paper will first provide institutional background information, before continuing to a literature review of relevant research in Sections 2 and 3, respectively. In Section 4, I discuss the datasets, variables of interest, and summary statistics. Section 5 details the empirical strategies, and Section 6 presents the results, which are broken down into subsections that separately address analyses and discussion of the findings. Finally, Section 7 summarizes the findings and implications, in addition to suggesting areas for future research.

II. Institutional Background

Often, barriers to employment faced by ex-offenders may be due to pre-existing, weak labor market characteristics, such as low skill, less education, and lack of work experience. While this may hold true in a number of cases, Pager (2003) demonstrates in a matched-pairs experimental study that employers discriminate against those with a criminal record, all other observable characteristics held equal. This reflects many employers' perceptions that candidates with criminal backgrounds may be less dependable employees and that the employers themselves may be liable for personal and legal consequences if a worker commits a crime during employment. Additionally, many jobs are restricted from ex-offenders, as a large number of state and federal municipalities ban those with felony convictions from certain occupations, licenses, and certifications (Solinas-Saunders et al., 2015). Employment opportunities for ex-offenders tend to be bleak, as they are not only prohibited from a number of occupations, but also face statistical discrimination in hiring. Particularly because a large concentration of ex-offenders is Black, the lack of employment opportunities for ex-offenders has important implications on employment disparities across race.

In recent years, many states have taken steps in attempt to increase employment opportunities for ex-offenders through collateral consequence relief mechanisms. One policy, "Ban-the-Box" (BTB) has recently been adopted across many states in the public sector and increasingly in the private sector. These policies prevent employers from including the check box that asks if candidates have a criminal record in job applications. Hawaii was the first to adopt a BTB policy in 1998, and many states have followed suit, with increasing expansion across states in the last several years. As of October 2020, 36 states, the District of Columbia, and over 150 cities and counties have adopted BTB policies in the public sector. Of those, 14 states and 20 cities and counties have expanded BTB policies to the private sector as well, resulting in seventy-five percent of the U.S. population living under BTB jurisdiction (Avery & Lu, 2020). BTB policies are aimed at encouraging ex-offenders to enter the labor force by lowering barriers in hiring decisions. It is implemented under the assumption that with less information, employers are able to make initial hiring judgements with equal opportunity by judging candidates based on qualification, rather than the presence or absence of criminal history. It should be noted that BTB does not prevent employers from being able to check the criminal history of potential candidates, but only limits them to accessing candidates' previous criminal convictions post-job application and review, delaying when they receive information about criminal background. The intention is to allow ex-offenders and non-offenders to be evaluated on a level playing field in the first step of the employment-seeking process.

Additionally, some states have also adopted Certificates of Rehabilitation/Restoration (COR), in which ex-offenders can obtain or apply for a document issued by a court that signals to employers that they are ready for employment. The certificate offers employers legal recognition that an individual with a COR deserves a second chance (Radice, 2011). In doing so, the legal risk of hiring an ex-offender is deflected on to the court rather than the employer, who bears a significantly less chance of being sued for negligence if an employee commits a crime. As of 2018, only 16 states and Washington D.C. have adopted COR policies, with the programs varying significantly across states in terms of both the process of document obtainment and implementation. New York's certificate program is the most well established and often a model for adoption of COR programs. Its program also allows for the restoration of eligibility of certain occupations to ex-offenders that they were previously prohibited from (McCann et al., 2018).

III. Literature Review

III.A Ban-the-Box ("Fair Chance") Policies

General employment effects

There has been an increasing amount of literature documenting the unintended consequences of BTB policies, with young, unskilled Black men experiencing the largest effects. With lack of information on criminal history, employers may rely on statistical discrimination and race-based assumptions to identify which candidates are more likely to be ex-offenders. As young, Black men tend to be associated with incarceration, BTB policies could hurt the employability of Black male population, regardless of offender status.

Two important pieces of literature using experimental and quasi-experimental evidence document that BTB policies negatively impact employment outcomes for young Black men (Agan & Starr, 2018; Doleac & Hansen, 2020). Agan and Starr (2018) investigate BTB's effects in New Jersey and New York City using a field experiment, in which approximately 15,000 fictitious online job applications were submitted to employers before and after the effective dates of private-sector BTB laws in the respective jurisdictions. The applications were sent in matched pairs with either a distinctly white or Black name. The study finds that before implementation of the BTB law, white applicants with the box had 7% more callbacks than corresponding Black applicants and that the disparity increased to 43% after the BTB law went into effect (Agan & Starr, 2018). The six-fold increase in callback disparity is attributed to increased use of race as a proxy for criminal history. This finding is supported by a quasi-experimental study, which used the variation in timing of BTB policies across states to assess effects on employment outcomes (Doleac & Hansen, 2020). Doleac and Hansen (2020) evaluate employment outcomes before and after implementation of BTB policies across 34 states and the District of Columbia, finding that BTB decreases the probability of employment by 3.4% for young, low-skilled Black men and by 2.3% for young, low-skilled Hispanic men.[1] The researchers also find that there may be a substitution effect, in which after BTB, employers may substitute away from hiring young, low-skilled Black and Hispanic men and toward older, low-skilled Black and Hispanic men (Doleac & Hansen, 2020). Overall, these two studies provide strong evidence that BTB policies have unintended consequences on employment outcomes, with the negative effects falling particularly heavily on young, unskilled marginalized males. These effects have important implications, as contrary to perceived expectations, BTB may actually increase racial disparities in employment outcomes.

[1] While BTB policies evaluated by Doleac and Hansen (2020) range across 34 states, not all of the policies considered were state policies, i.e. some states only had BTB policies within a county or city that did not apply to the entire state.

BTB policies' negative impact on employment outcomes for young Black men demonstrate evidence of statistical discrimination that is consistent with literature on lack of information in labor markets. When there is a lack of information available about potential candidates, employers tend statistically discriminate, using other factors such as race, prior salary, age, and skill as proxies. Studies have shown that availability of information, such as criminal records, drug testing, and credit scores increase employment rates of Black jobseekers (Doleac, 2019). Thus, given greater information, employers may be more comfortable hiring individuals who are typically discriminated against due to legitimate confirmation of candidates' reliability and history.

Employment effects for ex-offenders

Some may be able to tolerate the unintended consequences of BTB policies on employment outcomes if they are exceedingly successful in their purpose — increasing the employment prospects of ex-offenders; however, it may not be the case that they do. Two studies linked administrative datasets on employment and criminal record to evaluate ex-offenders' labor market outcomes following implementation of BTB policies (Jackson & Zhao, 2017; Rose, 2020). One study examining changes after a BTB policy came into effect in Seattle compared employment outcomes for ex-offenders in Seattle and in similar jurisdictions unaffected by the Seattle BTB policy. The study found that the BTB policy had negligible effects on employment and earnings of ex-offenders (Rose, 2020). Similarly, Jackson and Zhao (2017) use a difference-in-differences strategy to evaluate BTB policies in Massachusetts, finding that it actually had a small negative effect on ex-offenders' employment, with the negative effect growing over time. They suggest that the negative effect may be due to supply-side factors, in which ex-offenders perceive employment barriers to be lower and seek better working conditions or higher wages (Jackson & Zhao, 2017).

Additionally, since BTB does not prevent, but rather delays employers from accessing candidates' criminal histories, ex-offenders may face higher search costs. Rather than being rejected in the initial application process, employers could reject ex-offenders much later in the process once obtaining criminal background information, increasing the search cost for ex-offender candidates. This would lead to an increased population of discouraged workers among ex-offenders, thereby also contributing to supply-side factors in decreased probability of employment. Overall, whereas BTB policies are implemented with the intent to increase employment of ex-offenders, the studies described above demonstrate that they play a small and even adverse role in employment assistance.

III.B Certificates of Rehabilitation (Restoration)

In addition to BTB policies, some states have attempted to lower employment barriers through implementation of certificate programs; however, research on the effects of certificates of rehabilitation on ex-offender employment is sparse. This is likely because COR programs are relatively new mechanisms for relieving the collateral consequences of incarceration and because the process and nature of COR programs vary widely across these states. Qualitative research on COR programs has demonstrated the potential of COR programs to decrease collateral consequences; however, there is deep variation in processing and awarding the certificates across judges, probation officers, and other actors, which attributes to inefficiencies in the system (Ewald, 2016; Garretson, 2016).

Initial experimental studies on the effectiveness of CORs have shown promising results. In an experimental study following implementation of Ohio's COR equivalent, Leasure and Anderson (2016) submitted fictitious resumes to employers in pairs, varying only in an affirmative statement of a criminal record and an accompanying certificate. The researchers found that applicants with certificates were three times more likely to receive interview invitations or job offers and that there was no statistical difference between applicants with no criminal record and identical applicants with a criminal background and a certificate (Leasure & Andersen, 2016). In a later study by the same researchers, Leasure and Andersen (2020) conducted a similar experiment with a racial component, finding that there is a disparity between effectiveness of certificates between white applicants and Black applicants. White applicants with certificates received a positive response rate of over two times greater than Black applicants with certificates. While COR programs seek decrease racial disparities in labor market outcomes, they appear to be more effective for white ex-offenders.

III.C Contribution

This paper builds upon Doleac and Hansen's (2020) work by reexamining the effects of BTB on employment outcomes across gender, age, and race through an additional event-study analysis and updated data. Since the publication of their paper, 29 additional states and the District of Columbia (Table 1) have either newly adopted or expanded state-wide BTB policies, so reanalyzing the policies with additional recent data may provide new insights from a long-term and wider geographical perspective. As BTB policies have become increasingly popular and encompassing, it is important to leverage data updates to clearly understand potentially negative implications of the policy. Next, I will conduct a similar analysis for COR programs to evaluate potential impact of COR programs on employment outcomes across race, skill, and gender. Currently, nineteen states and the District of Columbia have implemented COR or COR equivalent

TABLE 1. BAN-THE-BOX POLICIES

State	Sector	Date	State	Sector	Date
Arizona	Public	November 6, 2017	Nebraska	Public	July 18, 2014
California	Public	June 25, 2010	Nevada	Public	January 1, 2018
	Private	October 1, 2020	New	Public	September 22, 2020
Colorado	Public	August 8, 2012	New Jersey	Public	March 1, 2015
	Private	September 1, 2021		Private	March 1, 2015
Connecticut	Public	January 1, 2017	New Mexico	Public	May 19, 2010
	Private	January 2, 2017		Private	June 14, 2019
Delaware	Public	November 4, 2014	New York	Public	September 21, 2015
Georgia	Public	February 23, 2015	North Dakota	Public	August 1, 2019
Hawaii	Public	July 15, 1998	Ohio	Public	March 23, 2016
	Private	July 15, 1998	Oklahoma	Public	February 24, 2016
Illinois	Public	October 3, 2013	Oregon	Public	January 1, 2016
	Private	January 1, 2015		Private	January 1, 2016
Indiana	Public	July 1, 2017	Pennsylvania	Public	July 1, 2017
Kansas	Public	May 2, 2018	Rhode Island	Public	January 1, 2014
Kentucky	Public	February 1, 2017		Private	January 1, 2014
Louisiana	Public	August 1, 2016	Tennessee	Public	April 14, 2016
Maine	Public	September 17, 2019	Utah	Public	May 8, 2017
Maryland	Public	October 1, 2013	Vermont	Public	April 21, 2015
	Private	January 1, 2020		Private	July 1, 2017
Massachusetts	Public	November 4, 2010	Virginia	Public	March 23, 2020
	Private	November 4, 2010	Washington	Public	June 7, 2018
Michigan	Public	October 1, 2018		Private	June 7, 2018
Minnesota	Public	January 1, 2009	Wisconsin	Public	July 1, 2016
	Private	January 1, 2014	District of	Public	January 1, 2011
Missouri	Public	April 11, 2016		Private	July 14, 2014

Notes: Information about timing and details about Ban-the-Box policies is drawn primarily from the National Employment Law Project in a report compiled by Avery and Lu 2020. This table is updated with information up to October 2020. Information marked in red shows sectors and policies that were not included in the study conducted by Doleac and Hansen (2020).

policies (Table 2). I build upon the work of Leasure and Anderson (2016) by conducting a difference-in-differences analysis for Ohio's COR equivalent to generalize employment outcomes to outside of the ex-offender population.

IV. Data

This paper uses individual-level data from Current Population Survey (CPS) to collect information on employment, race, age, skill, and other variables of interest. The CPS is a cross-sectional survey collected on a monthly basis and includes detailed information from about 60,000

TABLE 2. CERTIFICATES OF RESTORATION OR EQUIVALENT

State	Title	Citation
Alabama	Order of Limited Relief	Ala. Code § 12-26-1 - §12-26-11
Arizona	Restoration of Civil Rights	AZ Rev Stat § 13–912.01
Arkansas	N/A	§ 17-1-103
	Certificate of Completion	§ 11-2-123
California	Certificate of Rehabilitation	Penal Code § 4852.01-4852.21:
Colorado	Order of Collateral Relief	CO Rev Stat § 18-1.3-107
Connecticut	Certificate of Rehabilitation	§ 54-130(a) & 54-130€
District of Columbia	Certificates of Good Standing	§ 24-1304
Georgia	Program Treatment and Completion Certificate	Ga. Code Ann. § 42-2-5.2; § 51-1-54
Illinois	Certificate of Good Conduct	730 ILCS 5/5-5.5/25; 730 ILCS 5/5-5.5-30
	Certificate of Relief From Disabilities	730 ILCS 5/5-5.5-10; 730 ILCS 5/5-5.5-15; 730 ILCS 5/5-5-5
Iowa	Certificates of Employability	Iowa Admin. Code 205-9.1-9.4(906)
Maryland	Certificate of Rehabilitation	MD Code, Correctional Services, § 7-104
Michigan	Certificate of Employability	Mich. Comp. Laws § 791.234d
New Jersey	Certificate of Rehabilitation	N.J.S.A. 2A:168A-7
New York	Certificate of Good Conduct	N.Y. Correct. Law §§ 700(a)-(b)
	Certificate of Relief From Disabilities	N.Y. Correct. Law §§ 700-703
North Carolina	Certificate of Relief	N.C. Gen. Stat. § 15A–173.2(a).
Ohio	Certificate of Qualification for Employment	Ohio Rev. Code Ann. §§ 2952.25
	Certificate of Achievement and	Ohio Rev. Code Ann. §§ 2961.21-24
Rhode Island	Certificate of Recovery and Reentry	Rhode Island Chapter 13-8.2
Tennessee	Certificate of Employability	Tenn. Code Ann. § 40-29-107.
Vermont	Order of Limited Relief	Vt. Stat. Ann. tit. 13, § 8010
	Certificate of Restoration of Rights	Vt. Stat. Ann. tit. 13, § 8011
Washington	Certificate of Restoration of Opportunity	RCW § 9.97.010, .020

Notes: Information above was drawn primarily from McCann et al. (2018), Table 1. Some states have implemented COR policies since the publishing of the aforementioned study. To account for policies enacted since, this study used resources provided by the Restoration of Rights Project (n.d.), which details updated state-by-state policies related to the restoration of rights.

U.S. households, such as employment, education, health insurance, household data, and other demographics. Participants are only counted if they are 15 years or older. The data is primarily focused on employment information and is used monthly to provide estimates of the unemployment rate. As such, it contains a large dataset on individuals with information that is particularly relevant for examining employment outcomes. This survey has been conducted since 1940 by the U.S. Census Bureau for the Bureau of Labor Statistics. It was significantly redesigned

TABLE 3. BAN-THE-BOX SUMMARY STATISTICS

Variables	Non-Hispanic Black (n = 450,799)		Non-Hispanic White (n = 2,545,895)		Hispanic (n = 579,818)	
Public BTB policy	0.599	(0.490)	0.583	(0.493)	0.646	(0.478)
Private BTB policy	0.111	(0.314)	0.128	(0.334)	0.114	(0.318)
Age	38.91	(14.58)	40.36	(14.50)	35.52	(13.50)
Male	0.444	(0.497)	0.482	(0.500)	0.483	(0.500)
No high school diploma	0.176	(0.381)	0.112	(0.315)	0.360	(0.480)
High school diploma or eq.	0.530	(0.499)	0.428	(0.495)	0.449	(0.497)
College degree or more	0.293	(0455)	0.460	(0.498)	0.191	(0.393)
Employed	0.583	(0.493)	0.693	(0.461)	0.615	(0.487)
Northeast	0.169	(0.375)	0.238	(0.426)	0.167	(0.373)
Midwest	0.185	(0.389)	0.306	(0.461)	0.127	(0.333)
South	0.537	(0.499)	0.231	(0.421)	0.123	(0.328)
West	0.109	(0.311)	0.225	(0.418)	0.584	(0.493)

Notes: Note that monthly CPS data is cross-sectional, so the sample may include multiple observations for the same individual across different months.

in 1994, improving the quality of data collected and making the data more readily accessible to researchers (Polivka, 1996).

In Doleac and Hansen's (2020) paper, the researchers consider policies effective between 2004 to December 2014. The BTB section of my paper expands upon their research by extending the data to include policies effective by October 2020, with data extending from 2007-2020. An extended analysis may be insightful because initial adopters of policies aimed at benefiting ex-offenders are likely to be left-leaning jurisdictions. Thus, with expanded data, it is possible to better account for possible selection bias affecting empirical analyses of the data.

I examine information such as race, age, educational attainment, and employment in Table 3. The distinction between public and private sector is made because some states only adopted BTB policies for public and publicly contracted employment, while others adopt them in both the public and private sector. Across the sample, about 60% of the observations are under the jurisdiction of a public BTB policy, while about 12% of the observations are under the jurisdiction of a private BTB policy. Notable differences across races are education and geographic area, in which whites have higher average educational attainment and are generally spread out evenly across US regions, with a slightly higher concentration in the Midwest. In contrast, non-Hispanic Blacks are highly concentrated in the South, and Hispanics are highly concentrated in the West.

The COR analysis will aim to look more specifically at Ohio's Certificate of Qualification for Employment (CQE). Experimental evidence has already demonstrated that Ohio's CQE program has a significant effect on employment for ex-offenders and that the employment outcomes are disproportionate in benefits across race (Leasure & Andersen, 2016, 2020). Evidence that the program has an effect on ex-offender employment outcomes makes Ohio's CQE program attractive for broader analysis of its impact across race and skill with samples unconfined to ex-offenders; however, the drawback of this approach lies in the fact that Ohio may not be a representative sample that can be extrapolated to dissimilar areas of the United States. For example, compared to the U.S. average, Ohio's population tends to have a higher concentration of whites and a lower concentration of Hispanics.

Variables of interest for the COR analysis are summarized in Table 4. About 45% of the sample in both Ohio are observed when the COR policy is in effect. Correspondingly, the same proportion of observations in Michigan are observed after implementation of the COR policy in Ohio. Within-race characteristics between Ohio and Michigan are generally comparable, with Michigan having slightly higher average educational attainment and a slightly lower proportion of employed individuals. Compared to the BTB sample, which is more representative of the US average, the Ohio and Michigan samples have lower education attainment, with a higher proportion of observations who have no high school diploma and a lower proportion of observations who have college degrees. Additionally, the COR sample has a slightly lower

TABLE 4. CERTIFICATE OF RESTORATION SUMMARY STATISTICS

Variables	Ohio				Michigan			
	Non-Hispanic Black (n = 28,900)		**Non-Hispanic White (n = 221,251)**		**Non-Hispanic Black (n = 30,709)**		**Non-Hispanic White (n = 178,865)**	
COR policy in effect	0.455	(0.498)	0.445	(0.497)	0.445	(0.497)	0.444	(0.497)
Age	38.14	(14.57)	40.14	(14.49)	38.81	(14.70)	40.42	(14.60)
Male	0.438	(0.496)	0.483	(0.500)	0.433	(0.495)	0.486	(0.500)
No high school diploma	0.213	(0.410)	0.130	(0.347)	0.202	(0.402)	0.123	(0.329)
High school diploma or eq.	0.568	(0.495)	0.525	(0.500)	0.559	(0.497)	0.511	(0.500)
College degree or more	0.219	(0.413)	0.336	(0.472)	0.239	(0.427)	0.366	(0.482)
Employed	0.550	(0.498)	0.674	(0.469)	0.487	(0.500)	0.645	(0.478)

Notes: Summary statistics of observations in Ohio from 2008-2016. Note that monthly CPS data is cross-sectional, so there may be multiple observations across months for the same individual.

proportion of employed observations. This analysis focuses on differences between non-Hispanic Blacks and non-Hispanic whites, as the dataset for Hispanics lacks a large enough sample size for substantive analysis.

For consistency in analysis of outcomes, definitions of variables remain constant across datasets. An individual is coded as "employed" if they reported working in the previous week or did not work but acknowledged temporary absence from a job. I only consider those who are employed in the public or private sector, dropping anyone who considers themselves as self-employed, as they presumably did not gain employment though a hiring process. Additionally, given that 15 is the minimum age eligible for the CPS and 64 is considered age of retirement, only observations of individuals between ages 15-64 are considered in the original sample. The analysis is restricted to individuals who are non-Hispanic white, non-Hispanic Black, and Hispanic, hereafter referred to as "white," "Black," and "Hispanic," respectively. Native Americans are omitted from the sample due to small sample size, and as Asians are not often considered marginalized communities that are significantly affected by racial employment discrimination, they are not included in the analysis. Additionally, due to complexity of analysis, those who identified as more than two ethnicities or races are excluded from the sample. Using the "educ" variable available from IPUMS CPS data to identify skill-level of individuals, I categorized individuals into three categories, dropping observations (n = 13) that left "educ" blank: "no high school diploma," "high school diploma or equivalent," and "college degree or more." Individuals who fall into the latter category are considered highly skilled, and individuals who fall into the first two categories are considered low-skilled.

The sample set is constructed from data limited to specific time periods. Observations are restricted to those that occurred within either 24 months prior to or 30 months subsequent to implementation of either a public BTB or private BTB policy. For the purpose of this paper, only low-skilled individuals who are 24-35 are considered for two reasons. First, this group is the main population of interest in the study conducted by Doleac and Hansen (2020). For ease of comparison and consistency, the population of interest for this paper remains the same. Second, incarceration is typically associated with the younger, low-skilled population, particularly males. Effects on employment outcomes due to policies affecting ex-offenders are likely to be the greatest within this group.

V. Empirical Strategy

V.A Ban-the-Box Analysis

I analyze the effects of the BTB policy through a series of event-study regressions. This analysis tracks trends on a biannual basis for four periods both pre- and post-implementation. By normalizing all trends to time "zero," it is possible to see the average trend across all implementations of BTB policies, regardless of in which sector it was implemented. To do this, I construct a linear probability model using the following specification:

$$employed_{ist} = \alpha + \sum_{k=-4, k\neq-1}^{k=4} \varphi_k(event_{k,st}) + \delta_t + \gamma_s + \varepsilon_{ist} \quad (1)$$

φ_k estimates the average employment probability for $event_{k,st}$. $event_{k,st}$ is a dummy variable that indicates if, for individual i in state s and time t, BTB is in effect in either the public or private sector. Estimates of φ_k are calculated for each period of time relative to the year before the respective BTB policy has been implemented ($k = 0$). This model provides estimates for four periods prior to implementation as well as four periods post-implementation, where ($k = -1$) is forced to be zero to account for collinearity. Each period spans 6 months, with the model covering data for a total of 54 months for each respective implementation date of a BTB policy. Lastly, δ_t accounts for year fixed effects to account for common shocks over time and γ_s accounts for fixed effects to control for all time-invariant characteristics specific to states.

V.B Certificates of Rehabilitation Analysis

To analyze the effect of Certificates of Rehabilitation, I look specifically at Ohio's Certificate of Qualification for Employment and compare to areas demographically similar to Ohio, but not under the jurisdiction of a COR policy. Using a few sources online that analyze state similarity based on demographics such as partisanship, education, religion, suburbia, age, income, industry, and more, I narrowed down potential control states to Indiana, Michigan, Missouri (Jarman, 2020; Silver, 2008). Michigan was ultimately selected as the control due to a high similar score and consistent employment pre-trend in comparison to that of Ohio.

Analysis of the CQE's effect on employment outcomes is conducted through a difference-in-differences analysis. As aforementioned, a difference-in-differences analysis relies on two key identifying assumption: parallel trends and no anticipation of the policy. These assumptions are in turn addressed in Section 7 of this paper. The COR analysis is conducted using the following linear probability model:

$$Employed_{it} = \alpha + \beta_1 post_t + \beta_2(treat_m * post_{mt}) + \delta_t + \gamma_m + \varepsilon_{imt} \quad (2)$$

The CQE policy was implemented on September 29, 2012, and time period examined looks at employment trends for a total of 54 months, similar to the BTB analysis. For the difference-in-differences analysis, the "post periods," as defined in the BTB data section, will constitute the entire post-period dummy variable, and the "pre periods" will constitute the pre-period dummy variable. In the specification, β_2 is the "difference-in-differences" coefficient, or the coefficient of interest that predicts the impact of the CQE on average employment probability relative to the control. $post_{mt}$ indexes treatment of the CQE for the area m at time t, and $treat_m$ indexes whether area m has ever implemented CQE in the sample time period. This means that any county within Ohio will have an indicator value of 1 for $treat_m$, and any county within the control will have a respective indicator value of 0. δ_t accounts for year fixed effects to account for common shocks over time and γ_m accounts for fixed effects to control for all time-invariant characteristics specific to metropolitan area. Note that Michigan enacted a Certificate of Employability effective on January 1, 2015, which is a COR equivalent. The analysis in this paper extends to March 2015, which includes the beginning of Michigan's COR program enactment. This analysis assumes that the first few months of the program has negligible effects on overall employment due to initial implementation and organizational barriers, so the overlap is unlikely to significantly affect the regression coefficients.

V.C Expected Results

Based on existing literature that has documented the unintended consequences of BTB policies, I expect to find a decrease in employment probability for young, low-skilled Black individuals following implementation of the policy. Since there has been a large increase in the number of states that have recently implemented BTB policies, I expect to find a more pronounced negative effect of BTB policies in general; however, it may be possible that BTB policies may have less negative or even positive effects for Black individuals in southern areas. This is because there is a larger population of Black workers in the South, so it may be more difficult for employers to statistically discriminate. In response to BTB policies, I hypothesize that we may see employment increase among young, unskilled Black women in response to BTB policies, as employers may substitute towards candidates who they perceive to be less likely to have a criminal record.

Additionally, I hypothesize that the effects of Ohio's CQE on employment will differ from those of BTB policies. Since COR policies do not restrict information from employers, but rather reinforce productive capabilities of rehabilitated ex-offenders, it is more likely that the policy will lead to either negligible or positive effects on employment outcomes. These effects are likely reinforced by the shifting of liability of hiring ex-offenders from employers to the judicial courts.

On account of the seemingly opposing effects of BTB and COR policies, I hypothesize that that having a COR policy in place may counteract the negative consequences of BTB laws. This hypothesis will be explored in a preliminary analysis focusing specifically on Ohio in Section 7.

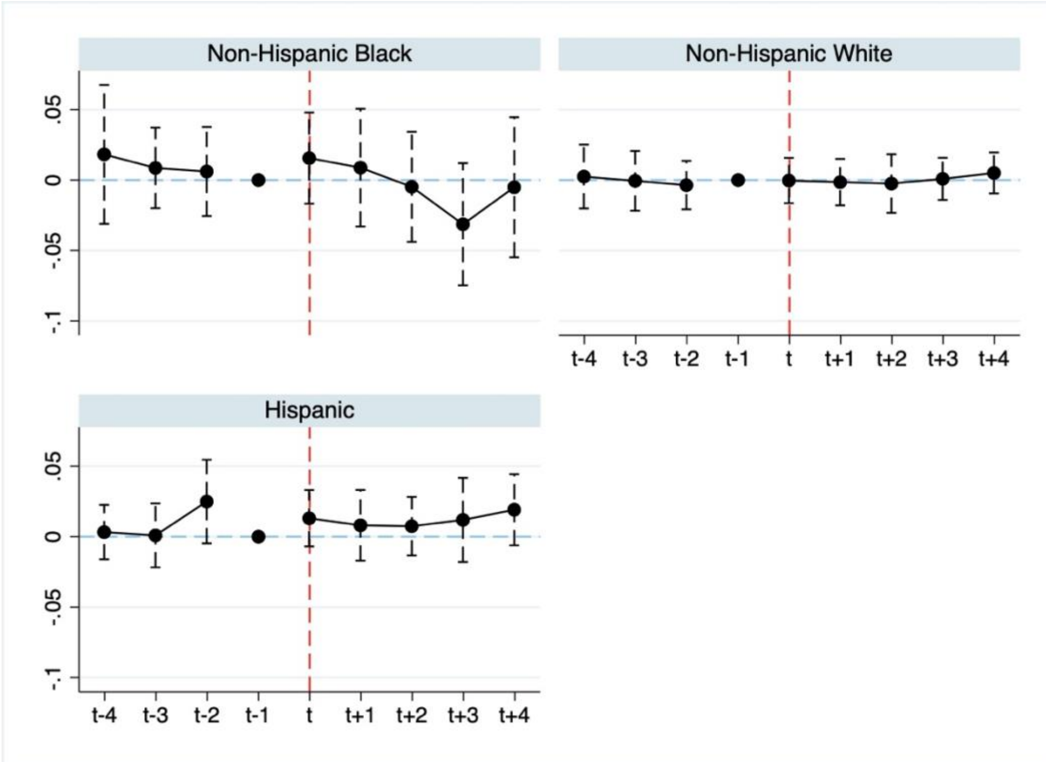

FIGURE 1. ESTIMATED AVERAGE EMPLOYMENT PROBABILITY FOR LOW-SKILLED MEN, AGES 24-34

Notes: CPS individual-level data from 2007-2020. The x-axis displays time period, where *t* represents time relative to adoption of BTB in the public or private sector. Each time period is 6 months; for example, $t + 1$ is 6-12 months post-implementation. The y-axis measures the estimated average probability of employment. Confidence intervals are calculated at $p = 0.05$. The graph plots coefficients from an event-study regression, restricting each sample to the population of interest. Note that the construction and design of Fig. 1 and subsequent graphs was partially drawn from a replication document provided by supplemental materials of Doleac and Hansen (2020).

VI. Analysis

VI.A Ban-the-Box Data Update

Results

Fig. 1 presents findings for males across race, where the x-axis represents time relative to implementation and the y-axis represents probability of employment. As noted earlier, the point at $t - 1$ is forced to be 0, since it is the omitted category within the event study regression. The dashed bars mark 95% confidence intervals. It appears that BTB policies do not appear to have a

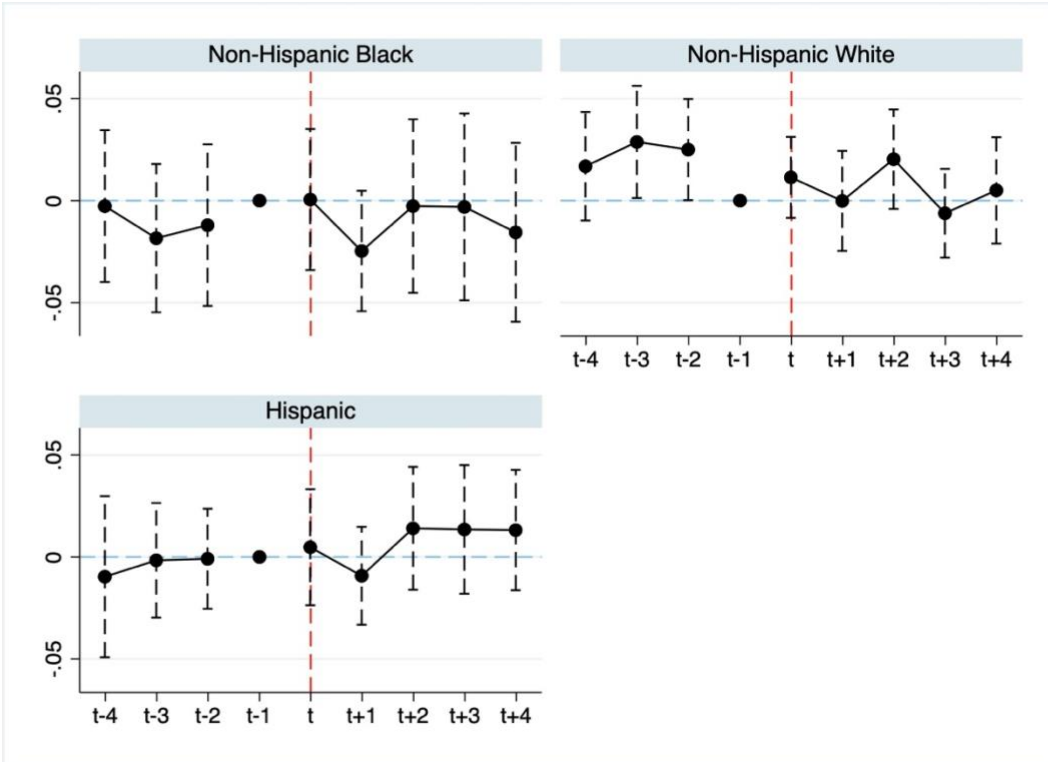

FIGURE 2. ESTIMATED AVERAGE EMPLOYMENT PROBABILITY FOR LOW-SKILLED WOMEN, AGES 24-34

Notes: CPS individual-level data from 2007-2020. The x-axis displays time period, where *t* represents time relative to adoption of BTB in the public or private sector. Each time period is 6 months; for example, $t + 1$ is 6-12 months post-implementation. The y-axis measures the estimated average probability of employment. Confidence intervals are calculated at $p = 0.05$. The graph plots coefficients from an event-study regression, restricting each sample to the population of interest.

statistically significant effect on employment across the three populations; however, while the estimates are noisy, there seems to be a downwards-sloping trend for Black men, where probability of employment increases just before implementation of the policy and steadily decreases for three time periods after implementation. For white men, estimates of the effect of BTB seem to straddle zero, pointing towards negligible effects. Interestingly, estimates for effects on Hispanic men seem to be generally positive, with slightly increased average probability of employment over time, suggesting that there may be substitution effects away from Black men and towards Hispanic men. Similar trends appear in the estimates of BTB across race for females, although the estimates have more variability and noise.

Fig. 2 presents estimates of BTB on Black, white, and Hispanic females. Among females, although estimates do not present significant effects of the BTB policies, they demonstrate general trends of negative effects among Black women, positive effects among Hispanic women, and fluctuating effects among white women. Given the slightly negative effect seen in Fig. 1 for Black men, we would generally expect to see increases in average probability of employment due to either substitution effects or intrahousehold decisions. First, if employers are hesitant to hire young, unskilled Black men following adoption of BTB, we would expect substitution towards workers with similar backgrounds but who are less likely to be ex-offenders. As females tend to be less associated with incarceration than males, adoption of BTB would reasonably lead to increased employment of young, unskilled females. Second, if Black males are experiencing more difficulty finding work, we would also expect to see an "added-worker" effect, where the partner may seek work in the face of falling partnership or family income. Both of these effects would lead to increased probability of employment for females; the lack of such trend suggests that BTB may have negligible, rather than negative, effects on employment outcomes for Black men.

A consistent effect between Fig. 1 and Fig. 2 is the generally opposing effects of BTB on average probability of employment for Black individuals compared to Hispanic individuals. To examine this more closely, Fig. 3 breaks down estimates for Hispanic (left) and Black (right) males by region in the U.S. If employers are substituting towards Hispanic males, then we would expect to see a greater positive change in employment probability for Hispanics in regions where there are greater negative changes in employment probability for Blacks. Once broken down by region, an expected trend due to substitution does not seem to appear, except partially in the Northeast. Given that there are no clear patterns across these graphs, it is unlikely that positive estimates for Hispanics are due to substitution following adoption of BTB. In fact, the positive estimates seem

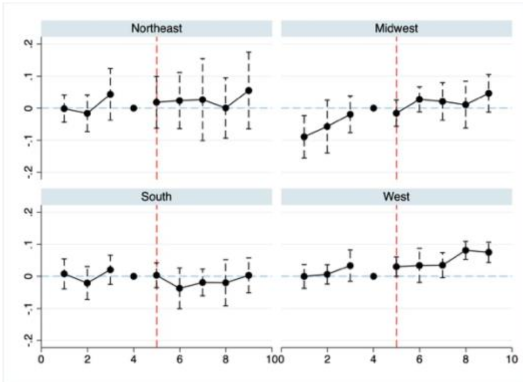

Fig. 3a

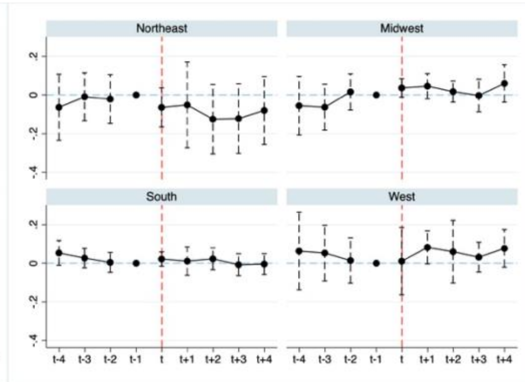

Fig. 3b

FIGURE 3: ESTIMATED AVERAGE EMPLOYMENT PROBABILITY FOR LOW-SKILLED HISPANIC (LEFT) AND BLACK (RIGHT) MEN, AGES 24-34

Notes: CPS individual-level data from 2007-2020. The x-axis displays time period, where t represents time relative to adoption of BTB in the public or private sector. Each time period is 6 months; for example, $t + 1$ is 6-12 months post-implementation. The y-axis measures the estimated average probability of employment. Confidence intervals are calculated at $p = 0.05$. The graph plots coefficients from an event-study regression, restricting each sample to the population of interest.

to largely be driven by the Western region. We see that there are statistically significant increases in employment probability for Hispanic men in the West, consistent with the idea that a larger population of Hispanics in the West may restrict employers from the ability to statistically discriminate. This explanation, however, does not hold consistent across the other three regions. In particular, we still see positive effects for Hispanic males in the Midwest, a region where they are the least concentrated within the US. Similarly, there does not appear to be a difference in effect in relation to population concentration for Black males, as the majority of Black individuals live in the South, and there is a negligible effect. Rather, the negative effect appears to be driven by estimates in the Northeast.

Discussion

Despite Ban-the-Box policies being implemented to assist ex-offender in finding employment, recent studies have demonstrated that benefits to ex-offenders are negligible.

Furthermore, experimental studies have provided evidence that BTB policies have a negative effect on Black males, largely due to statistical discrimination. This paper uses variation in timing of private sector and public sector BTB policies to evaluate effects on employment outcomes. While we would expect BTB policies to increase average employment probability for Black individuals due to the disproportionately large population of Black ex-offenders, this paper reinforces the trend of non-positive effects of BTB on employment outcomes for Black individuals. While the results provide unclear conclusions about whether BTB policies have decreased employment probability for Black individuals, they demonstrate that they likely have, at most, negligible outcomes. One different finding from this study, however, is that there seems to be a slightly positive increase in average employment outcome for Hispanics, although there is not a clear, external explanation as to why that is. This outcome, along with the lack of negative results for young, unskilled Black and Hispanic men, differs slightly from the findings of Doleac and Hansen (2020).

There are two likely explanations for the difference in findings. The first is that with updated data, especially due to recent large-scale expansions of BTB policies into the private sector, the results may naturally appear different. With many states having adopted or expanded BTB policies since the authors' paper was written, a larger set of data may actually tell a different story. The second, and more likely, explanation for the difference is due empirical decisions and internal validity. The model and specifications run by Doleac and Hansen (2020) take into account factors such as time trends, metropolitan-statistical-area-specific time trends, and a number of other demographic areas that this paper was unable to account for. Additionally, whereas Doleac and Hansen (2020) only considered the implementation of BTB in the public sector as an event date of interest, this paper attempts to also account for adoption of BTB policies in the private sector.

Doleac and Hansen (2020) coded an observation as "treated" if there was any BTB policy in effect under the jurisdiction in which the individual resided, leading to only public sector implementation dates being considered since it precedes any implementation of private sector policies. The decision to include private sector implementation dates of BTB policies in this paper is based on the fact that the large majority of workers are employed in the private sector, so the respective BTB policy is more likely to affect individuals' ability to be employed. If the assumption made by Doleac and Hansen (2020) that the public sector BTB implementation date is more of interest than private sector BTB dates, then including observations that account for private sector dates would lead to an upwards bias, as seen in this study. This upwards bias would result if fixed time effects did not capture the general trend of increasing employment rates over time, biasing estimates of average employment probability upwards.

VI.B Analysis of Ohio's Certificate of Qualification for Employment Program

Results

The first step in this analysis was to conduct a pre-trend analysis. As seen in Fig. 4, the average employment between 2010 and the implementation date for Ohio and Michigan appear to be increasing at around the same rate. In the beginning of 2012, there appears to be a slight decrease in average employment, but the trend remains largely the same until the effective date of Ohio's CQE policy.

The second key identifying assumption in a difference-in-difference analysis is that there is no substantial reaction to anticipation of the policy. Generally speaking, it is unlikely that anticipation of the policy would result in significant changes in employment because it does not directly affect employers. That is, the mechanism of the policy works through the applicant-side

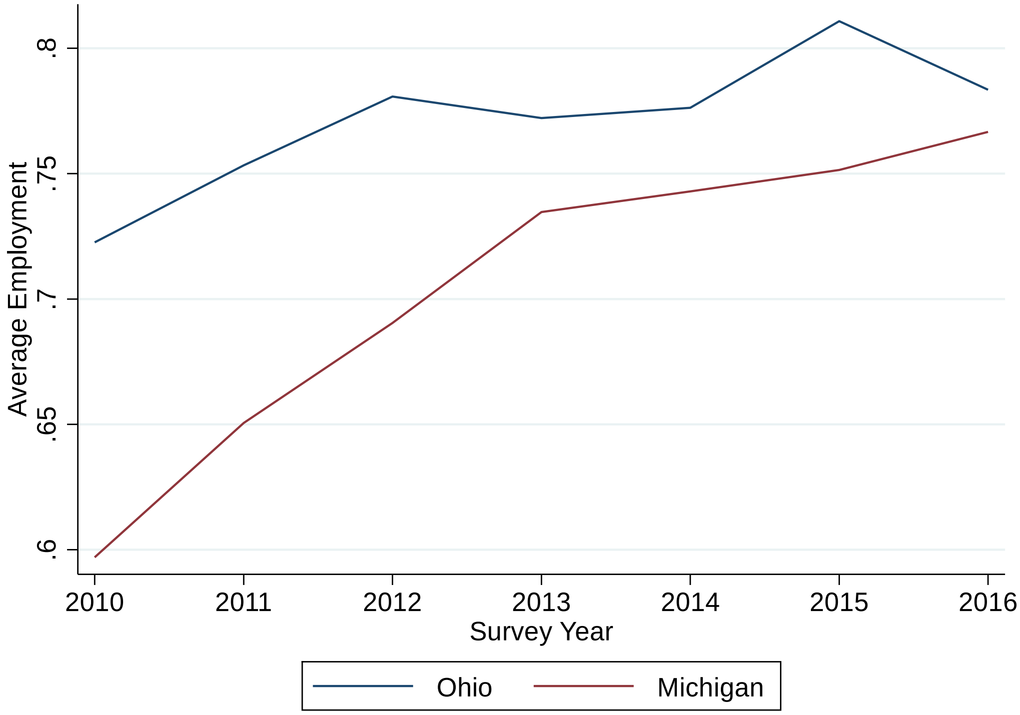

FIGURE 4. AVERAGE EMPLOYMENT FOR LOW-SKILLED MEN, AGES 24-34 IN TREATMENT AND CONTROL GROUP

Notes: CPS individual-level data from 2010-2016. The x-axis displays year, where the vertical line represents the effective date of the Ohio Certificate of Qualification for Employment policy (September 19, 2012). The y-axis measures average employment. Due to sample size, the sample is restricted to only Black and white individuals.

by aiding ex-offenders in their job-searching process and largely does not affect employers until they encounter an applicant with a CQE; however, a less likely scenario in which employers may react to this policy is if they know that their applicants are typically ex-offenders. In this case, employers may hold off on hiring until there is a pool of applicants with CQEs to make a safer hiring decision. This is unlikely to affect the following analysis because the approval process to obtain a CQE can take up to 60 days (Ohio Department of Rehabilitation & Correction, n.d.). Given the length of the approval process, a long period of time would likely need to elapse before employers encounter multiple applicants with CQEs. Accordingly, employer reactions are more likely to occur after implementation rather than prior to implementation. As such, anticipatory

TABLE 5. DIFFERENCE-IN-DIFFERENCES ANALYSIS FOR LOW-SKILLED MEN, AGES 24-34

VARIABLES	White		Black	
	(1)	**(2)**	**(1)**	**(2)**
treat x post	-0.0281**	-0.0255	-0.133***	-0.101*
	(0.0131)	(0.0172)	(0.0375)	(0.0568)
post	0.0536***	0.0509***	0.0421	0.0352
	(0.0152)	(0.0150)	(0.0429)	(0.0362)
treat	0.0639***	0.0544***	0.155***	0.417***
	(0.00732)	(0.00545)	(0.0198)	(0.0228)
Constant	0.713***	0.719***	0.508***	0.374***
	(0.00654)	(0.00411)	(0.0167)	(0.0109)
Observations	20,485	20,485	3,416	3,416
R-squared	0.016	0.021	0.026	0.057
Sample	Whites	Whites	Blacks	Blacks
Metro FE	No	Yes	No	Yes
Metro Cluster	No	Yes	No	Yes
Number of Clusters		23		23

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: CPS individual-level data from 2010-2016. Due to small sample size for Hispanics, the sample is restricted to only Black and white individuals.

reactions to the CQE implementation, if they occur, are not likely to affect the difference-in-difference analysis.

Next, a formal difference-in-difference analysis is conducted to examine the effect of the CQE policy on employment over time (Table 5). The table above displays the results of the regressions, in which each regression differs in sample and controls. Column (2) displays the most relevant regressions, which account for fixed effects across metropolitan area and cluster by metropolitan area. Between the pre-period and post-period, employment grew by about 5.09 percentage points across the control and treatment group for whites and by about 3.52 percentage points for Blacks. The coefficients on the variable of interest, *treat x post*, measures the difference-in-differences. The results point towards an insignificant effect of the CQE policy on employment for both whites and Blacks, where there is a 2.55-point decrease in employment relative to the control for whites with a p-value > 0.1, and a 10.1-point decrease in employment relative to the control for Blacks with a p-value < 0.1. It is notable, however, that the number of observations for Blacks in this sample is very low, so the coefficients are very sensitive and subject to low statistical significance.

Discussion

While there does appear to be a change in employment for both white and Black individuals, that there is no statistically significant change is unsurprising. As described in the literature review, early studies of the effect of Certificates of Rehabilitation have demonstrated positive employment effects for ex-offenders. In accordance with previous literature on the asymmetric information surrounding employment decisions, more information about the candidate likely does not lead to greater discrimination (Doleac 2019). Because this policy does not restrict information from employers, we would not expect a statistically significant decline in employment for individuals similar to general demographics of ex-offenders. Rather, given preliminary studies on the beneficial outcomes of COR programs for ex-offenders (Leasure & Andersen, 2016), we could possibly expect an increase in employment among individuals examined in the analysis, subject to the number of ex-offenders in Ohio. Thus, it is surprising that the difference-in-difference analysis demonstrated a 10.1 percentage point decrease in employment for low-skilled, Black individuals relative to the control group; however, given the small sample size and lack of statistical significance, it is difficult to draw any concrete conclusions based on the coefficients.

This analysis is subject to a few limitations, namely due to data restrictions regarding the control group. As mentioned earlier, Michigan enacted a Certificate of Employability policy effective on January 1, 2015. While Michigan was selected as a control due to very similar employment pre-trends, the policy restricted data analysis to span a shorter period of time than intended. Thus, because the data only spans 54 months, the sample size is not ideal to draw statistically significant conclusions about the coefficients. Additionally, because the time period examined in the analysis extends to around March 2015, it includes a portion of data in Michigan that are affected by a similar COR policy as that in Ohio; however, because the judicial process of obtaining a COR is long, any effect should be rather small. If there is an effect, then Michigan's employment trend for low-skilled, young Black men would likely be biased upward, leading to a larger negative coefficient on *treat x post*.

VI.C Relationship between BTB and of CQE Policies in Ohio

Results

On March 23, 2016, Ohio passed a public Ban-the-Box policy, about 4 years following the implementation of the Certificate of Qualification for Employment. Given previous literature that has documented potentially harmful employment effects of BTB on individuals similar in demographic to ex-offenders, it is possible that these negative or negligible effects differ when a Certificate policy is in effect. It is possible that CQEs actually counteract the effects of BTB in the later stages of the hiring process, through mechanisms that will be detailed in the next section.

To explore the potential relationship, I examine specifically the effect of BTB on employment outcomes in Ohio. The analysis conducted is similar to that specified in equation (1), where the sample is restricted to Ohio. Fig. 5 examines the effect of BTB on low-skilled, young Black men in Ohio compared to both the average effect in Ohio and compared to the US average. It appears that in Ohio, employment probability for low-skilled, young Black men had a statistically significant increase in periods t + 2, t + 3, and t + 4. Compared to the change in

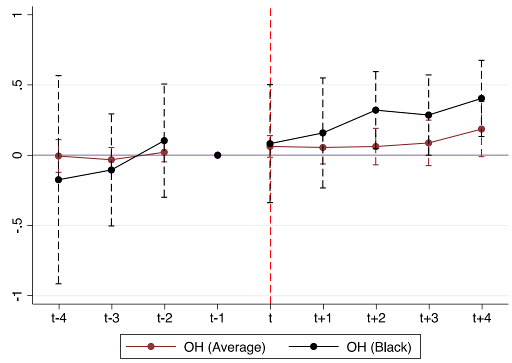

Fig. 5a

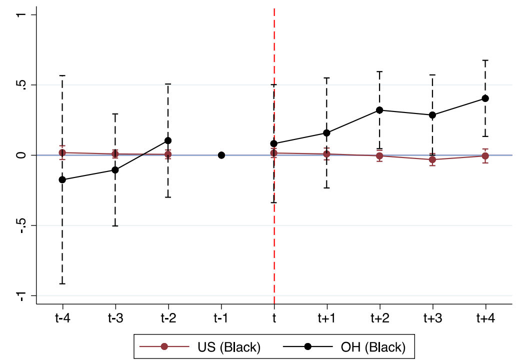

Fig. 5b

FIGURE 5. ESTIMATED AVERAGE EMPLOYMENT PROBABILITY FOR LOW-SKILLED, BLACK MEN IN OHIO COMPARED TO OHIO AVERAGE (LEFT) AND US BTB AVERAGE (RIGHT), AGES 24-34

Notes: CPS individual-level data from 2007-2020. The x-axis displays time period, where t represents time relative to adoption of BTB in the public or private sector. Each time period is 6 months; for example, $t + 1$ is 6-12 months post-implementation. The y-axis measures the estimated average probability of employment. Confidence intervals are calculated at $p = 0.05$. The graph plots coefficients from an event-study regression, restricting each sample to the population of interest.

employment probability for Ohio across races, it appears that there is no statistical difference, although the trendline for Black individuals is consistently above that of the average. Although there is not a statistically significant difference, it is interesting that Black individuals in Ohio largely do not appear to be negative impacted by the implementation of the BTB policy. Fig. 5b paints a similar picture, in that the trendline for Black individuals in Ohio lies consistently above that of the average for Black individuals in states that have implemented a BTB policy. In fact, for periods t + 2 and t + 4, there is a statistically significant difference between estimated employment probability for Blacks in Ohio and Blacks in the US. At the 90% confidence level, the difference is statistically significant for period t + 3 as well (Fig A1). Additionally, it seems that in the post-period, the trend lines between Blacks in Ohio and the average effect for Blacks begin to diverge. These results suggests that the presence of the COR policy prior to implementation of BTB laws possibly account for some of the difference in employment outcomes between Blacks in Ohio and the US average.

Discussion

The findings support the notion that Ban-the-Box laws and Certificates of Rehabilitation may have opposing effects on employment outcomes for individuals who are similar in demographic to ex-offenders. It appears that the trend line for low-skilled, Black individuals in Ohio lies consistently above that for the average in Ohio and the same group across states that have employed BTB laws. It is possible that this pattern is not coincidental, but rather the consequence of a COR policy already in place when Ohio adopted BTB laws.

This paper proposes two mechanisms through which a COR policy could counteract the negative effects of BTB laws. The first is directly through increased employment of ex-offenders. According to the Prison Policy Initiative, Blacks represent about 12% of the population, yet 43% of the incarceration population (Jones, 2018). It follows that ex-offenders in Ohio are also overwhelmingly Black and are strongly affected by the CQE policy. Because the CQE affirms the employability of ex-offenders, it shifts legal risk of ex-offender recidivism during employment from the employer to the court that approved the Certificate. If it is largely beneficial to ex-offenders, as detailed by Leasure and Anderson (2016), then increased hiring among ex-offenders could explain relatively greater employment probability for low-skilled, young Black individuals in Ohio.

The second mechanism in which COR policies could possibly counteract negative effects of BTB laws is through destigmatization. COR policies have been demonstrated to be effective in removing some of the barriers of employment for ex-offenders. As ex-offenders who are able to gain employment through COR policies more efficiently reenter society, they likely increasingly interact with a larger number of non-ex-offenders. As this occurs, it is possible that employment of ex-offenders becomes less stigmatized, producing spillover effects among employers by decreasing statistical discrimination following implementation of BTB policies.

It should be noted that the graphs do not depict a formal analysis of the relationship between COR policies and BTB laws. Rather, it specifically focuses on how employment effects of BTB laws differ among comparison groups, so there may be other factors driving the possible differences. Additionally, this analysis only pertains to Ohio, which cannot be demographically extrapolated to the general US population. The analysis above simply posits potential mechanisms that could possibly explain a relationship between differing employment outcomes of COR policies and BTB laws.

VII. Conclusion

This paper examines how two recent policies designed to reduce employment barriers for ex-offenders has affected overall employment for individuals demographically similar to ex-offenders. Specifically, it examines employment effects across low-skilled, young white, Black, and Hispanic individuals. Employing event study analyses, this paper first gives a data update on the effects of Ban-the-Box laws based on Doleac and Hansen (2020). Previous literature has documented unintended consequences of BTB laws, in that when facing a lack of information, employers rely on statistical discrimination and race-based assumptions to make hiring decisions (Agan & Starr, 2018; Doleac & Hansen, 2020). Because low-skilled, young Black individuals are overrepresented in incarceration facilities and the ex-offender population, individuals of similar demographic in the non-ex-offender population are hurt by this policy. In addition, existing literature has demonstrated that these negative effects are not outweighed by positive employment effects for ex-offenders. In fact, they have small, or even adverse, effects on employment for ex-offenders (Jackson & Zhao, 2017; Rose, 2020). Using updated data, this paper is consistent with existing research by demonstrating that there are, at most, negligible effects of BTB laws on average employment effects for low-skilled, young Black males and females. It also demonstrates that in the face of BTB adoption, employers do not appear to be substitution towards Hispanic individuals of similar backgrounds. As aforementioned, the data approach in this analysis differs from that of Doleac and Hansen (2020). This is due to both independent data decisions and lack of access to specific details on the authors' analysis. Further analysis can more closely compare the analysis of Doleac and Hansen (2020) with the current data by breaking down the effects of BTB implementation for both the private and public sector. Additional research can also formally test for differences between groups of interest. That is, while the figures in this paper allow for visual comparison of trend lines, it does not formally test if the outcomes are significantly different from one another.

In addition to BTB laws, this paper adds to the growing literature around the effects of Certificates of Rehabilitation. The utilization of COR programs as a tool to combat collateral consequences of incarceration is not very widespread, and there is large variation between states that have adopted these policies system (Ewald, 2016; Garretson, 2016). Likewise, research on the effectiveness of these policies is nascent, but initial experimental studies have demonstrated promising effects of COR policies (Leasure & Andersen, 2016, 2020). To the best of my knowledge, this is the first paper to examine employment effects of COR policies outside of the ex-offender population. Examining specifically the existing Certificate of Qualification for Employment program in Ohio, this paper uses a difference-in-differences analysis to quantify employment changes in the general population. I find that, as expected, adoption of CQE did not have statistically significant effects on employment of low-skilled, young white or Black individuals compared to the control. This is likely because the CQE provides employers with more information about the candidates, so statistical discrimination is unlikely to increase. Further analysis could use a synthetic control method, as detailed by (Abadie, forthcoming). This method takes advantage of data from areas demographically similar to the treatment group to construct a synthetic data set, projecting a trendline for the control group following implementation of a policy.

Finally, this paper explores the potential relationship on employment outcomes between BTB laws and COR policies. Because both policies are designed to benefit the ex-offender population, it is possible that together, they have a unique effect. Indeed, while there are not statistically significant results, in Ohio, where BTB laws were adopted after a COR policy was in place, low-skilled, young Black individuals appeared to have a higher average probability of employment than other comparison groups. This paper proposes two mechanisms through which this could have taken place: directly through the increase of ex-offender employment and indirectly through destigmatizing employment of ex-offenders. These analyses are only preliminary, however, as it only examines samples specifically from Ohio. Further analyses could take a look at other states that have similarly adopted both BTB and COR policies to better understand their joint effects on employment.

The focus of this paper was on general employment effects in response to recent policies designed to lower barriers to ex-offender employment. Average probability of employment was the main variable of interest throughout the analyses of this paper. While examining the supply-side of employment is important, it would be interesting to understand how demand-side factors that change in response to BTB and COR policies. Previous literature has concluded that BTB policies have led to increased statistical discrimination, but this analysis was largely drawn from experiments from the applicants' perspectives. Future studies may benefit from understanding decisions that the employers face following implementation of BTB and COR policies from a more qualitative perspective. These perspectives may shine light on how employment decisions are made by firms, providing insight into how to better anticipate consequences of future policies affecting employment of ex-offenders.

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Appendix

TABLE A1. ESTIMATED AVERAGE EMPLOYMENT PROBABILITY FOR LOW-SKILLED MEN, AGES 24-34

Variables	Non-Hispanic Black	Non-Hispanic White	Hispanic
$t-4$	0.0183	0.00249	0.0032
	(0.0243)	(0.0112)	(0.00951)
$t-3$	0.00862	-0.000557	0.000867
	(0.0141)	(0.0104)	(0.0112)
$t-2$	0.00607	-0.0036	0.0249*
	(0.0156)	(0.00846)	(0.0146)
$t-1$	0	0	0
t	0.0156	-0.000344	0.013
	(0.0159)	(0.00793)	(0.00986)
$t+1$	0.00881	-0.00147	0.00804
	(0.0206)	(0.00813)	(0.0124)
$t+2$	-0.00477	-0.00247	0.00741
	(0.0192)	(0.0102)	(0.0102)
$t+3$	-0.0314	0.000875	0.0119
	(0.0213)	(0.00737)	(0.0147)
$t+4$	-0.00509	0.00506	0.0191
	(0.0245)	(0.00716)	(0.0124)
Constant	0.642***	0.778***	0.803***
	(0.0132)	(0.00595)	(0.00789)
Observations	26,029	114,742	52,031
R-squared	0.024	0.014	0.018
Year FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Cluster by State	Yes	Yes	Yes
Number of Clusters	36	36	36

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Regression results from Figure 1. CPS individual-level data from 2007-2020. Confidence intervals are calculated at p = 0.05. Each time period is 6 months; for example, $t+1$ is 6-12 months post-implementation. The coefficients are from an event-study regression, restricting each sample to the population of interest.

TABLE A2. ESTIMATED AVERAGE EMPLOYMENT PROBABILITY FOR LOW-SKILLED WOMEN, AGES 24-34

Variables	Non-Hispanic Black	Non-Hispanic White	Hispanic
$t-4$	-0.00267	0.0169	-0.0097
	(0.0183)	(0.0131)	(0.0195)
$t-3$	-0.0184	0.0288**	-0.00164
	(0.0179)	(0.0135)	(0.0138)
$t-2$	-0.012	0.0250**	-0.000897
	(0.0195)	(0.0122)	(0.0121)
$t-1$	0	0	0
t	0.000518	0.0114	0.00478
	(0.0170)	(0.00978)	(0.0140)
$t+1$	-0.0247*	-0.000161	-0.00923
	(0.0145)	(0.0121)	(0.0118)
$t+2$	-0.00269	0.0203*	0.014
	(0.0210)	(0.0120)	(0.0148)
$t+3$	-0.00309	-0.00621	0.0135
	(0.0226)	(0.0107)	(0.0155)
$t+4$	-0.0156	0.00503	0.0132
	(0.0216)	(0.0128)	(0.0145)
Constant	0.607***	0.607***	0.553***
	(0.0137)	(0.00850)	(0.00972)
Observations	32,120	95,862	50,261
R-squared	0.022	0.013	0.013
Year FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Cluster by State	Yes	Yes	Yes
Number of Clusters	36	36	36

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Regression results from Figure 2. CPS individual-level data from 2007-2020. Confidence intervals are calculated at p = 0.05. Each time period is 6 months; for example, $t + 1$ is 6-12 months post-implementation. The coefficients are from an event-study regression, restricting each sample to the population of interest.

TABLE A3. ESTIMATED AVERAGE EMPLOYMENT PROBABILITY FOR LOW-SKILLED HISPANIC AND BLACK MEN, AGES 24-34

VARIABLES	Non-Hispanic Black				Hispanic			
	Northeast	**Midwest**	**South**	**West**	**Northeast**	**Midwest**	**South**	**West**
$t-4$	-0.0633	-0.0551	0.0534*	0.0631	-0.0016	-0.0892**	0.0078	-0.000163
	(0.0741)	(0.0672)	(0.0282)	(0.0822)	(0.0184)	(0.0292)	(0.0206)	(0.0151)
$t-3$	-0.00918	-0.0628	0.0266	0.0528	-0.0162	-0.0573	-0.0208	0.00622
	(0.0539)	(0.0525)	(0.0223)	(0.0590)	(0.0247)	(0.0364)	(0.0227)	(0.0123)
$t-2$	-0.0207	0.0162	0.00431	0.0141	0.0431	-0.0193	0.0204	0.0333
	(0.0548)	(0.0413)	(0.0227)	(0.0480)	(0.0348)	(0.0253)	(0.0200)	(0.0199)
$t-1$	0	0	0	0	0	0	0	0
t	-0.064	0.0369	0.0218	0.0107	0.0181	-0.0157	0.00329	0.0300*
	(0.0437)	(0.0209)	(0.0163)	(0.0711)	(0.0351)	(0.0181)	(0.0170)	(0.0124)
$t+1$	-0.0513	0.0462	0.0111	0.0822*	0.0234	0.0274	-0.0372	0.034
	(0.0962)	(0.0288)	(0.0325)	(0.0347)	(0.0380)	(0.0173)	(0.0280)	(0.0216)
$t+2$	-0.125	0.0176	0.0227	0.0596	0.0264	0.0208	-0.0191	0.0348*
	(0.0779)	(0.0240)	(0.0253)	(0.0663)	(0.0554)	(0.0258)	(0.0184)	(0.0160)
$t+3$	-0.122	-0.00292	-0.00762	0.0313	0.000541	0.0107	-0.02	0.0811***
	(0.0782)	(0.0372)	(0.0251)	(0.0315)	(0.0407)	(0.0323)	(0.0317)	(0.0115)
$t+4$	-0.0799	0.0602	-0.00435	0.0770*	0.055	0.0463	0.00308	0.0748***
	(0.0763)	(0.0429)	(0.0238)	(0.0396)	(0.0520)	(0.0259)	(0.0241)	(0.0129)
Constant	0.689***	0.631***	0.638***	0.608***	0.762***	0.876***	0.881***	0.770***
	(0.0478)	(0.0221)	(0.0147)	(0.0356)	(0.0259)	(0.0154)	(0.0150)	(0.00892)
Observations	4,005	5,432	13,530	3,062	7,669	6,770	7,298	30,294
R-squared	0.028	0.026	0.022	0.07	0.023	0.014	0.013	0.01
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by State	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Clusters	9	10	10	7	9	10	10	7

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: Regression results from Figure 3. CPS individual-level data from 2007-2020. Confidence intervals are calculated at p = 0.05. Each time period is 6 months; for example, $t + 1$ is 6-12 months post-implementation. The coefficients are from an event-study regression, restricting each sample to the population of interest.

TABLE A4. ESTIMATED AVERAGE EMPLOYMENT PROBABILITY FOR LOW-SKILLED, BLACK MEN IN OHIO COMPARED TO OHIO AVERAGE AND US BTB AVERAGE, AGES 24-34

VARIABLES	**Ohio**	**Ohio Black**	**US Black**
$t-4$	-0.00574	-0.175	0.0183
	-0.0515	-0.321	-0.0243
$t-3$	-0.0322	-0.105	0.00862
	-0.0385	-0.173	-0.0141
$t-2$	0.0209	0.104	0.00607
	-0.0301	-0.175	-0.0156
$t-1$	0	0	0
t	0.0623	0.0822	0.0156
	-0.034	-0.182	-0.0159
$t+1$	0.055	0.158	0.00881
	-0.0519	-0.17	-0.0206
$t+2$	0.0616	0.321**	-0.00477
	-0.0574	-0.119	-0.0192
$t+3$	0.0876	0.286**	-0.0314
	-0.0717	-0.124	-0.0213
$t+4$	0.186*	0.404***	-0.00509
	-0.0866	-0.117	-0.0245
Constant	0.741***	0.494***	0.642***
	-0.0312	-0.134	-0.0132
Observations	6,403	862	26,029
R-squared	0.012	0.134	0.024
Year FE	Yes	Yes	Yes
State FE	Metro	Metro	State
Cluster by State	Metro	Metro	State
Number of Clusters	10	9	36

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Regression results from Figure 5. CPS individual-level data from 2007-2020. Each time period is 6 months; for example, $t + 1$ is 6-12 months post-implementation. Confidence intervals are calculated at $p = 0.05$. The coefficients are from an event-study regression, restricting each sample to the population of interest.

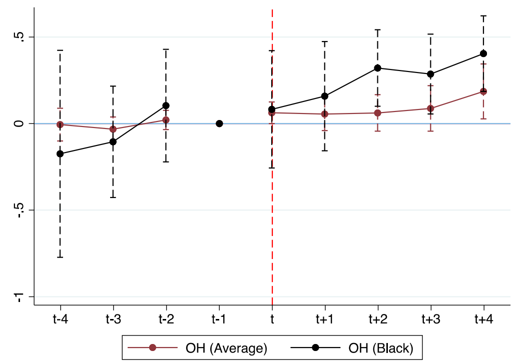

Fig. A1a

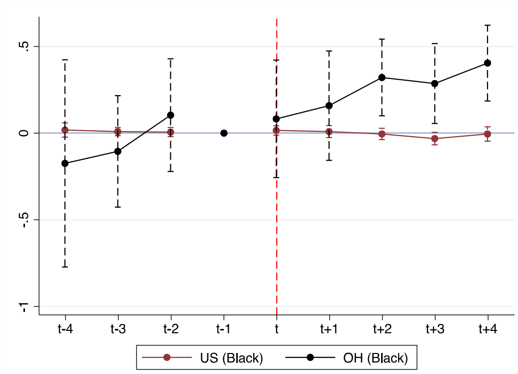

Fig. A1b

FIGURE A1. ESTIMATED AVERAGE EMPLOYMENT PROBABILITY FOR LOW-SKILLED, BLACK MEN IN OHIO COMPARED TO OHIO AVERAGE (LEFT) AND US BTB AVERAGE (RIGHT), AGES 24-34 [90% CI]

Notes: CPS individual-level data from 2007-2020. The x-axis displays time period, where t represents time relative to adoption of BTB in the public or private sector. Each time period is 6 months; for example, t + 1 is 6-12 months post-implementation. The y-axis measures the estimated average probability of employment. Confidence intervals are calculated at p = 0.10. The graph plots coefficients from an event-study regression, restricting each sample to the population of interest.

This graph corresponds to Figure 5, with confidence intervals plotted at the 90% level rather than the 95% level. At the 90% level, relative to period t – 1, there is a statistically significant increase in estimated average employment probability for Blacks in Ohio in periods t + 2, t + 3, and t + 4 (Fig. A1a). These are similar to the results from Fig. 5a, but the lower bound of the confidence intervals lie more clearly above zero. There is a statistically significant difference between estimated average employment probability for Blacks in Ohio and Blacks in the US in periods t + 2, t + 3, and t + 4 (Fig. A1b). This differs from Fig. 5, which only finds statistical difference for periods t + 2 and t + 4.