The unintended consequences of "ban the box": Statistical discrimination and employment outcomes when criminal histories are hidden

Jennifer L. Doleac^{*} and Benjamin Hansen[†]

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^{*}Frank Batten School of Leadership and Public Policy, University of Virginia, Charlottesville, VA 22904. Email: jdoleac@virginia.edu.

[†]Department of Economics, University of Oregon, Eugene, OR 97403. Email: bchansen@cas.uoregon.edu.

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Abstract

Jurisdictions across the United States have adopted "ban the box" (BTB) policies preventing employers from conducting criminal background checks until late in the job application process. Their goal is to improve employment outcomes for those with criminal records, with a secondary goal of reducing racial disparities in employment. However, removing information about job applicants' criminal histories could lead employers who don't want to hire ex-offenders to guess who the ex-offenders are, and avoid interviewing them. In particular, employers might avoid interviewing young, low-skilled, black and Hispanic men when criminal records are not observable, guessing that these applicants are more likely to be ex-offenders. This would exacerbate racial disparities in employment. In this paper, we use variation in the details and timing of state and local BTB policies to test BTB's effects on employment for various demographic groups. We find that BTB policies decrease the probability of being employed by 3.4 percentage points (5.1%) for young, low-skilled black men, and by 2.3 percentage points (2.9%) for young, low-skilled Hispanic men. These findings support the hypothesis that when an applicant's criminal history is unavailable, employers statistically discriminate against demographic groups that include more ex-offenders.

1 Introduction

Mass incarceration has been an important crime reduction policy for the past several decades, but it has come under intense scrutiny due to high financial cost, diminishing public-safety returns, and collateral damage to the families and communities of those who are incarcerated. There is substantial interest in reallocating public resources to more cost-effective strategies, with greater emphasis on rehabilitating offenders. Due in part to this change in focus, individuals are now being released from state and federal prisons more quickly than they are being admitted. According to the most recent data, over 637,000 people are released each year (Carson and Golinelli, 2014). However, recent data also suggest that approximately two-thirds of those released will be re-arrested within three years (Cooper et al., 2014). This cycle signals the country's failure to help re-entering offenders transition to civilian life, and limits our ability to reduce incarceration rates. Breaking this cycle is a top policy priority.

Both theory and evidence suggest that connecting ex-offenders with jobs can keep them from re-offending. The classic Becker (1968) model of criminal behavior suggests that better employment options reduce crime. In practice, increasing the availability of jobs for re-entering offenders reduces recidivism rates (Schnepel, 2015; Yang, 2017). But finding employment remains difficult for this group. Part of the reason ex-offenders have difficulty finding employment is that, on average, they have less education and job experience than non-offenders. However, as Pager (2003) and others have shown, employers discriminate against ex-offenders even when other observable characteristics are identical. This is likely due to statistical discrimination.¹ Ex-offenders are more likely than non-offenders to have engaged in violent, dishonest, or otherwise antisocial behavior, and – based on current recidivism rates – are more likely to engage in similar behavior in the future.² Ex-offenders also have higher rates of untreated mental illness, addiction, and emotional trauma (Raphael, 2010; Wolff and Shi, 2012; Justice Center, 2016). These are all valid concerns for employers seeking reliable, productive employees. But this reasoning is little comfort to someone coming out of prison

¹Some employers' discrimination could be taste-based – that is, they simply don't like ex-offenders, and no additional information about individuals with records could change their feelings. This distinction does not alter the predicted effects of "ban the box", but does matter when considering alternative policies.

 $^{^{2}}$ This not only affects an individual's expected tenure on the job, but increases potential financial costs to the employer. For instance, employers might worry about theft, or that future violent behavior could result in a negligent-hiring lawsuit.

and hoping to find gainful legal employment. In addition, since black and Hispanic men are more likely to have criminal records, making a clean record a condition for employment could exacerbate racial disparities in employment.³

If even a few ex-offenders are more job-ready than some non-offenders, then employers' statistical discrimination against those with criminal records hurts the most job-ready ex-offenders. This has motivated the "ban the box" (BTB) movement, which calls for employers to delay asking about an applicant's criminal record until late in the hiring process. Advocates of BTB believe that if employers can't tell who has a criminal record, job-ready ex-offenders will have a better chance at getting an interview. During that interview, they may be able to signal their otherwise-unobservable job-readiness to the employer. This could increase employment rates for ex-offenders, and thereby decrease racial disparities in employment outcomes.

However, this policy does nothing to address the average job-readiness of ex-offenders. A criminal record is still correlated with lack of job-readiness⁴. For this reason, employers will still seek to avoid hiring individuals with criminal records. When BTB removes information about a criminal record from job applications, employers may respond by using the remaining observable information to try to guess who the ex-offenders are, and avoid interviewing them. Even though ex-offenders could be weeded out after the interview process, interviewing candidates is costly. Employers would rather not spend time interviewing candidates that they are sure to reject when their criminal history is revealed. Surveys by Holzer et al. (2006) show that employers are most concerned about hiring those who were recently incarcerated. Since young, low-skilled, black and Hispanic men are the most likely to fall in this category (Bonczar, 2003; Yang, 2017), employers may respond to BTB by avoiding interviews with this group. Even black and Hispanic men without a record would lose opportunities with employers who are worried these applicants have a record but are forbidden from asking. As a result, racial disparities in employment could increase rather than decrease.

This paper estimates the effect of BTB policies on employment for young, low-skilled, black and Hispanic men. To do this, we exploit variation in the adoption and timing of state and local

³The best data available suggest that a black man born in 2001 has a 32% chance of serving time in prison at some point during his lifetime, compared with 17% for Hispanic men and 6% for white men (Bonczar, 2003).

⁴We use "job-readiness" to refer to a range of characteristics that make someone an appealing employee, including reliability and productivity.

BTB policies to test BTB's effects on employment outcomes, using individual-level data from the 2004-2014 Current Population Survey (CPS). We focus on the probability of employment for black and Hispanic men who are relatively young (age 25-34)⁵ and low-skilled (no college degree), as they are the ones most likely to be recently-incarcerated. This group contains the most intended beneficiaries of BTB as well as the most people who could be unintentionally hurt by the policy. If BTB does not exacerbate statistical discrimination by employers, and only helps ex-offenders, then we would expect BTB to increase employment among groups that include a lot of ex-offenders. If, however, BTB reduces employment for this group and no others, that is strong evidence that employers are statistically discriminating, and the damage to innocent bystanders within this group is greater than the aid given to ex-offenders.

We find net negative effects on employment for these groups: Young, low-skilled black men are 3.4 percentage points (5.1%) less likely to be employed after BTB than before. This effect is statistically significant (p < 0.05) and robust to a variety of alternative specifications and sample definitions. We also find that BTB reduces employment by 2.3 percentage points (2.9%) for young, low-skilled Hispanic men. This effect is only marginally significant (p < 0.10) but also fairly robust. Both effects are unexplained by pre-existing trends in employment, and – for black men – persist long after the policy change. The effects are larger for the least skilled in this group (those with no high school diploma or GED), for whom a recent incarceration is more likely.

We expect BTB's effects on employment to vary with the local labor market context. For instance, it would be difficult for an employer to discriminate against all young, low-skilled black men if the local low-skilled labor market consists primarily of black men, or if there are very few applicants for any open position. We find evidence that such differential effects exist. BTB reduces black male employment significantly everywhere but in the South (where a larger share of the population is black). Similarly, BTB reduces Hispanic male employment everywhere but in the West (where a larger share of the population is Hispanic). This suggests that employers are less likely to use race as a proxy for criminality in areas where the minority population of

 $^{^{5}}$ We follow the literature and focus on individuals age 25 and over because most individuals have completed their education by that age. In our sample, only about 1% of low-skilled men ages 25-34 are enrolled in school. Since we are using education level as a proxy for skill level, using final education increases the precision of our estimates (relative to, for instance, considering all 19 year olds "low-skilled" because they don't yet have a college degree).

interest is larger – perhaps because discriminating against that entire set of job applicants is simply infeasible. In addition, we find evidence that statistical discrimination based on race is less prevalent in tighter labor markets: BTB's negative effects on black and Hispanic men are larger when national unemployment is higher. In other words, employers are more able to exclude broad categories of job applicants in order to avoid ex-offenders when applicants far outnumber available positions.

Our hypothesis is that employers are less likely to interview young, low-skilled black and Hispanic men because these groups include a lot of ex-offenders with recent convictions and incarcerations. This hypothesis suggests that employers will instead interview and hire individuals from demographic groups unlikely to include recent offenders. We find some evidence suggesting that this does indeed happen. Older, low-skilled black men are significantly more likely to be employed after BTB.⁶ (This supports our hypothesis that the racial discrimination at work is statistical, not taste-based.) Effects on white men are also positive and significant when BTB targets private firms.

However, total employment might go down when employers are not able to see which applicants have criminal records. BTB increases the expected cost of interviewing job applicants, because there's a higher chance that any interview could end in a failed criminal background check. In addition, while employers might be willing to substitute college graduates or others who are clearly job-ready, those individuals might not be willing to accept a low-skilled job at the wage the employer is willing to pay.⁷ Consistent with this, we find no effect on employment for men with college degrees. Controlling for local unemployment rates has little effect on our estimates, suggesting that BTB simply shifts employment, rather than reducing it – at least in the short run.

We are not the only researchers interested in the effects of BTB on employment. Two other papers, written concurrently with this one, study the effect of this policy. However, ours is the only one to focus on real-world employment outcomes for young, low-skilled men – the group with the most to gain or lose from BTB.

Agan and Starr (2016) exploited the recent adoption of BTB in New Jersey and New York to conduct a field experiment testing the effect of the policy on the likelihood of getting an interview.

⁶Highly-educated black women are also more likely to be employed after BTB, but this effect could represent intrahousehold substitution, rather than substitution by employers. That is, women might be more likely to work when their partners are unable to find jobs.

⁷This is related to the well-known "lemons problem" in economics, where asymmetric information between a buyer and seller causes a market to unravel and no transactions to be made (Akerlof, 1970).

They submitted thousands of fake job applications from young, low-skilled men, randomizing the race and criminal history of the applicant. They found that before BTB white applicants were called back slightly more often than black applicants were. That gap increased six-fold after BTB went into effect. White ex-offenders benefited the most from the policy change: after BTB, employers seem to assume that all white applicants are non-offenders. After BTB, black applicants were called back at a rate between the ex-offender and non-offender callback rates from before BTB – that is, those with records were helped, but those without records were hurt. Since the researchers create the applications themselves, they could keep other factors like education constant. The differences in interview rates before and after the policy change are therefore solely due to the changing factors - race and criminal history. The limitation of this approach is that fake applicants can't do real interviews that lead to real jobs. It's possible that the few ex-offenders granted interviews would be more likely to get the job after BTB implementation than before. However, if employers are reluctant to hire ex-offenders, those applicants might be rejected once their criminal history is revealed late in the process (between the interview and the job offer). These later steps are critical in determining the true social welfare consequences of BTB. Our paper complements this one by showing that these changes in callback rates do result in changes in hiring, with a net negative effect on employment for young, low-skilled black men. We also confirm that young, low-skilled white men are more likely to get hired when BTB laws target private firms.

Shoag and Veuger (2016) use a difference-in-difference strategy to consider the effects of BTB on residents of high-crime neighborhoods (a proxy for those with criminal records), using those living in low-crime neighborhoods (a proxy for those without criminal records) as a control group. They focus on a subset of BTB cities (though they are not listed in the paper). Neighborhoods are deemed high- or low-crime based on violent crime rates in 2000, and employment is measured for 2002-2013. Using aggregated data, they find that more people are employed in high-crime neighborhoods after BTB, relative to employment in low-crime neighborhoods, and interpret this as evidence that BTB has a beneficial effect on ex-offenders. However, no effort is made to control for changes in the compositions of these neighborhoods over time, and the authors are unable to control for residents' demographic characteristics. It seems likely that the residents of both types of neighborhoods changed over the course of two economic downturns, the housing bubble, and the housing crash, and places that were high-crime in 2000 might not be by 2013. It is therefore unclear from this analysis who (if anyone) is benefiting from BTB. A supplementary analysis uses annual data from the American Community Survey (ACS) to consider effects of BTB on the full working-age population, divided by race and gender. They find a net increase in employment for black men. As in their previous analysis, they make no effort to break results down by education level or age, and so cannot test the effect of the policy on the groups most likely to be affected. In addition, the way the ACS asked about employment changed in 2008, and this change seems to have increased employment estimates (Kromer and Howard, 2010). It's unclear how the authors account for this, and so their finding that black employment increased after BTB could be an artifact of this change in the survey. Given concerns about the integrity of ACS employment data during this time period, the CPS is better suited to measuring the impact of BTB. We use the CPS to consider impacts on the groups most likely to be affected BTB, in the full set of BTB communities instead of a non-random subset. We also use individual-level data with a full set of demographic controls, to account for the composition of local labor markets.

Ban the box policies seek to limit employers' access to criminal histories. This access itself is relatively new. Before the internet and inexpensive computer storage became available in the 1990s, it was not easy to check job applicants' criminal histories. This is the world that BTB advocates would like to recreate. Of course this world differs from our own in many other respects, but nevertheless it is helpful to consider how employment outcomes changed as criminal records became more widely available during the 1990s and early 2000s. A number of studies address this, and their findings foreshadow our own: when information on criminal records is available, firms are more likely to hire low-skilled black men (Bushway, 2004; Holzer et al., 2006; Finlay, 2009; Stoll, 2009). In fact, many of those studies explicitly predicted that limiting information on criminal records, via BTB or similar policies, would negatively affect low-skilled black men as a group.⁸

⁸A few striking quotes from that literature:

[[]S]ome advocates seek to suppress the information to which employers have access regarding criminal records. But it is possible that the provision of more information to these firms will increase their general willingness to hire young black men, as we show here and since we have previously found evidence that employers who do not have such information often engage in statistical discrimination against this demographic group. (Holzer et al., 2004)

Employers have imperfect information about the criminal records of applicants, so rational employers may use observable correlates of criminality as proxies for criminality and statistically discriminate against groups with high rates of criminal activity or incarceration. (Finlay, 2009)

There is plenty of evidence that statistical discrimination increases when information about employees is less precise. Autor and Scarborough (2008) measure the effects of personality testing by employers on hiring outcomes. Conditioning hiring on good performance on personality tests (such as popular Myers-Briggs tests) was generally viewed as disadvantaging minority job candidates because minorities tend to score lower on these tests. However, the authors note that this will only happen if employers' assumptions about applicants in the absence of information about test scores are more positive than the information that test scores provide. If, in contrast, minorities score better on these tests than employers would have thought, adding accurate information about a job applicant's abilities will help minority applicants. They find that in a national firm that was rolling out personality testing, the use of these tests had no effect on the racial composition of employees, though they did allow the firm to choose employees who were more productive.

Wozniak (2015) found that when employers required drug tests for employees, black employment rates increased by 7-30%, with the largest effects on low-skilled black men. As in the personality test context, the popular assumption was that if black men are more likely to use drugs, employers' use of drug tests when making hiring decisions would disproportionately hurt this group. It turned out that a drug test requirement allowed non-using black men to prove their status when employers would otherwise have used race as a proxy for drug use.

In another related paper, Bartik and Nelson (2016) hypothesize that banning employers from checking job applicants' credit histories will negatively affect employment outcomes for groups that have lower credit scores on average (particularly black individuals). The reasoning is as above: in the absence of information about credit histories, employers will use race as a proxy for credit scores. They find that, consistent with statistical discrimination, credit check bans reduce job-finding rates by 7-16% for black job-seekers. As with BTB policies, one goal of banning credit checks was to reduce racial disparities in employment, so this policy was counterproductive.

Our study therefore contributes to a growing literature showing that well-intentioned policies

[[]Ban the box] may in fact have limited positive impacts on the employment of ex-offenders....More worrisome is the likelihood that these bans will have large negative impacts on the employment of those whom we should also be concerned about in the labor market, namely minority – especially black – men without criminal records, whose employment prospects are already poor for a variety of other reasons. (Stoll, 2009)

that remove information about racially-imbalanced characteristics from job applications can do more harm than good for minority job-seekers.⁹ Advocates for these policies seem to think that in the absence of information, employers will assume the best about all job applicants. This is often not the case. In the above examples, providing information about characteristics that are less favorable, on average, among black job-seekers – criminal records, drug tests, and credit histories – actually helped black men and black women find jobs. These outcomes are what we would expect from standard statistical discrimination models. More information helps the best job candidates avoid discrimination.

The availability of criminal records is just one facet of an ongoing debate about data availability. Improvements in data storage and internet access have made a vast array of information about our pasts readily available to those in our present, including to potential employers, love interests, advertisers, and fraudsters. This often seems unfair to those who – like many ex-offenders – are trying to put their pasts behind them. The policy debate about whether and how to limit this data availability is complicated both by free speech concerns and logistical issues – once information is distributed publicly, what are the chances of being able to make it private again? Even so, a great deal of effort has gone into defining who should have access to particular data, often with the goal of improving the economic outcomes of disadvantaged groups.¹⁰ As this and related studies have shown, well-intentioned policies of this sort often have unintended consequences, and providing more information is often a better strategy.

This paper proceeds as follows: Section 2 provides background on BTB policies. Section 3 describes our data. Section 4 presents our empirical strategy. Section 5 describes our results. Section 6 presents robustness checks. Section 7 discusses and concludes.

⁹An additional study focuses on a different population but its findings are consistent with the same statistical discrimination theory as those described above: Thomas (2016) finds that when the Family and Medical Leave Act limited employers' information about female employees' future work plans, it decreased employers' investment in female employees as a group. After the FMLA, women were promoted at lower rates than before the law.

¹⁰See for example, the "right to be forgotten" movement in Europe, which included a ruling that – at a person's request – search engines must "remove results for queries that include the person's name" (Google, 2016). See also the White House's recent recommendations on consumer data privacy, available at https://www.whitehouse.gov/sites/default/files/privacy-final.pdf.

2 Background on BTB policies

When allowed, employers commonly include a box on job applications that applicants must check if they have been convicted of a crime, along with a question about the nature and date(s) of any convictions. Anecdotally, many employers simply discard the application of anyone who checks this box. BTB policies prevent employers from asking about criminal records until late in the hiring process, when they are preparing to make a job offer. The first BTB law was implemented in Hawaii in 1998, and – as of December 2015 – similar policies exist in 34 states and the District of Columbia. President Obama "banned the box" on employment applications for federal government jobs in late 2015.

BTB policies fall into three broad categories: (1) those that target public employers (that is, government jobs only), (2) those that target private employers with government contracts, and (3) those that target all private employers. We'll refer to these as "public BTB", "contract BTB", and "private BTB" policies, respectively. Every jurisdiction in our sample with a contract BTB policy also has a public BTB policy. Similarly, every jurisdiction in our sample with a private BTB policy also has a contract BTB policy. Thirteen percent of jurisdictions adopt a contract and/or private BTB policy during this time period. Our analysis focuses primarily on the effects of having *any* BTB policy, but we consider differential effects by policy type in Section 5.5.

Public BTB laws can affect both public and private sector employment. These policies were typically implemented due to public campaigns aimed at convincing employers to give ex-offenders a second chance. Public BTB policies were intended in part to model the best practice in hiring, and there is anecdotal evidence that this model – in combination with public pressure – pushed private firms to adopt BTB even before they were legally required to. Several national private firms such as Wal-Mart, Target, and Koch Industries, voluntarily "banned the box" on their employment applications during this period, in response to the BTB social movement.¹¹

Public BTB laws might also affect private sector employment because workers are mobile between the two sectors, and likely sort themselves based on where they feel most welcome. Ex-offenders who

¹¹We do not consider the effects of those voluntary bans here, but do note that a principal-agent problem could lead to the same effects as for government bans. A CEO might be inclined to hire ex-offenders, but the managers who are actually making the hiring decisions might still want to avoid supervising individuals with criminal records.

would have been employed in the private sector might not get those jobs if they target job openings in the public sector due to a public BTB law; if applicants change their application strategies and where they spend their time interviewing for jobs, these such policies could quickly have meaningful impacts on private sector employment. Because BTB likely affected jobs in both sectors, we will focus on the net effect of BTB policies on the probability that individuals work at all. We believe this is the most relevant policy question. However, we also consider the effect of BTB on public-sector employment, specifically, in Section 6.3.

3 Data

Our analysis considers BTB policies effective by December 2014. Figure 1 maps the cities, counties, and states with BTB policies by that date.¹² Information on the timing and details of BTB policies comes primarily from Rodriguez and Avery (2016). The details of local policies used in this analysis are listed in Table 3. When information about a policy's effective date was available, we used that date as the start date of the policy; otherwise we used the date the policy was announced or passed by the legislature. If only the year (month) of implementation was available, we used January 1 of that year (the first of that month) as the start date.

Information on individual characteristics and employment outcomes comes from monthly Current Population Survey (CPS) data for 2004 through 2014.¹³ The CPS is a repeated cross-section that targets those eligible to work. It excludes anyone under age 15 as well as those in the Armed Forces or in an institution such as a prison. Each monthly sample consists of about 60,000 occupied households; the response rate averages 90 percent (CPS, 2016). Excluding those who are incarcerated could affect our analysis: If BTB increases recidivism and incarceration by making it more difficult to find a job, some of the people now unemployed because of the policy will be excluded from the CPS sample. Any such sample selection will bias our estimates upward, so that BTB

¹²Appendix Figure A-1 shows maps of BTB policies by year, for 2004 through 2014.

¹³We use the public-use CPS files available from the National Bureau of Economic Research (NBER). These raw data contain item non-response codes when a respondent did not answer a question, rather than imputed responses. Many studies use CPS data from the Integrated Public Use Microdata Series (IPUMS); in those files, all responses are fully cleaned and imputations replace non-responses. In light of increasing evidence of widespread non-response in surveys like the CPS, and the effect that imputations have on the accuracy and precision of empirical estimates (Meyer et al., 2015), we prefer the raw data, particularly for the relatively disadvantaged population of interest here.

policies look more helpful than they are.

The CPS provides information on age, sex, race, ethnicity, education level, and current employment (if employed, and employer type). Since our hypotheses center on statistical discrimination by race and ethnicity, we limit our analysis to individuals who are white non-Hispanic, black non-Hispanic, or Hispanic (hereafter referred to as white, black, and Hispanic, respectively). We consider three levels of educational achievement: no high school diploma, no college degree, and college degree.¹⁴ We code someone as "employed" if they answer yes to the question, "Last week, did you do any work for pay?" This should be the most reliable measure of employment for our population of interest, for whom temporary, seasonal, or informal jobs are common. We restrict our sample to those who are U.S. citizens, and who do not consider themselves retired.¹⁵

Our goal is to measure the effect of BTB on individuals in the local labor market, so we assign treatment at the level of Metropolitan Statistical Areas (MSAs). All individuals are matched to states, and about three-quarters are matched to MSAs.¹⁶ We consider individuals treated by BTB if their state has a BTB policy, or if any jurisdiction in their MSA has a BTB policy. For individuals living outside of an MSA, only state-level policies matter. To the extent that this approach codes some MSA residents as treated by BTB when they were not, this will bias our results toward finding no effect of the policy.

Our primary group of interest is young (ages 25-34), low-skilled (no college degree) men. We focus on this group for several reasons: (1) The age profile of criminal offenders is such that most crimes are committed by young men. In 2012, 60% of criminal offenders were age 30 or younger (Kearney et al., 2014). So, employers concerned about job applicants' future criminal behavior should be most concerned about younger individuals. (2) Employers report the most reluctance to hire individuals who were recently incarcerated (Holzer et al., 2004), and those who are recently

¹⁴In the CPS, these are determined using the "highest level of school completed or degree received" variable. For our purposes, no high school diploma means the respondent has up to 12 years of high school but no diploma or GED; no college degree means the respondent has up through some college but did not earn an associate degree or bachelor degree; college means the person has an associate degree or higher. Note that the no high school diploma category is a subset of the "no college degree" category; these are two ways to define low-skilled and we focus on the latter to maximize statistical power.

¹⁵The data also include whether the respondent reports being disabled and/or unable to work, but we use these variables with caution as they could be endogenous to local labor market conditions and individuals' employment prospects.

¹⁶About half of respondents are matched to counties. Running our analysis at the county-level yields qualitatively similar but less precise results.

released tend to be young because they were young when they were convicted.¹⁷ (3) The vast majority of ex-offenders have a high school diploma (or GED) or less.¹⁸

There are 855,772 men ages 25-34 in our sample; 503,419 of those have no college degree. In that subset, 11.9% are black, 14.0% are Hispanic, and the remaining 74.1% are white. Forty-six percent of the young, low-skilled men in our sample lived in areas that were treated by BTB as of December 2014.

Summary statistics for the full working-age male population (ages 25-64) in the CPS are shown in Table 1. Summary statistics for our primary population of interest – low-skilled men ages 25-34 – are presented in Table 2.

Individuals affected by BTB policies are not randomly distributed across the U.S. As Table 2 shows, those affected by BTB are much more likely to live in metro areas. Appendix Table A-1 shows the effect of pre-period (2000) state characteristics on the likelihood of at least one jurisdiction in that state adopting a BTB policy by December 2014. States with BTB policies are more urban, have more black residents, have more college-educated residents, and have residents with higher earnings. When all of these characteristics are considered together, the strongest predictor of having a BTB policy is having a larger black population, though this effect is small: a one percentage point increase in the state black population increases the probability that BTB is adopted in that state by 1.75 percentage points (2.5% of the average probability). The remaining characteristics are statistically insignificant.

We are particularly interested in whether the local labor markets in non-BTB places are good counterfactuals for those in places that adopted BTB. Focusing on metro areas only, we find that the local unemployment rate in 2000 has a weak relationship with the probability that an MSA ever adopted BTB: a one percentage point increase in local unemployment increases the probability of adopting BTB by only 1.5 percentage points, and that effect is statistically insignificant. Similarly, the local pre-period unemployment rate had a small and insignificant effect on the timing of BTB

¹⁷Individuals released from state prison between 2000 and 2013 were 35 years old, on average, and the standard deviation was 11 years (Yang, 2017).

 $^{^{18}}$ Fifty-two percent of those released from state prison between 2000 and 2013 had less than a high school degree, and 41 percent had a high school degree but no college degree. Only 1% of released offenders had a college degree (Yang, 2017). This is partly because many inmates have the opportunity to earn a GED while incarcerated, but college classes are typically unavailable.

adoption. Results are in Appendix Table A-2.

Overall, this is a policy that has been adopted primarily by urban areas in states with larger black populations, but the local labor market conditions do not appear to have affected whether or when BTB was adopted by particular jurisdictions. Even so, adoption of BTB was a local choice, and the results of this study speak to the effects of BTB in the types of jurisdictions that adopted the policy by December 2014. Given that areas that don't adopt BTB look somewhat different from those that do adopt BTB, we conduct robustness checks that use only similar jurisdictions as control groups. We also pay close attention to the "parallel trends" assumption of our differencein-difference identification strategy.

4 Empirical Strategy

We consider the effect of BTB policies on the probability that individuals are employed, based on a linear probability model. We use the following specification:

$$Employed_{i} = \alpha + \beta_{1}BTB * White_{m,t} + \beta_{2}BTB * Black_{m,t} + \beta_{3}BTB * Hispanic_{m,t} + \beta_{4}\delta_{MSA} + \beta_{5}D_{i} + \beta_{6}\lambda_{time*region} + \beta_{7}\delta_{MSA} * f(time)_{t} + e_{i},$$
(1)

where *i* indexes individuals. BTB * White, BTB * Black, and <math>BTB * Hispanic are the treatment variables. Since the sample includes *only* white, black, and Hispanic individuals, there is no excluded racial group (so no stand-alone BTB term is necessary). δ_{MSA} are MSA fixed effects. D_i is a vector of individual characteristics that help explain variation in employment, including race, ethnicity, age fixed effects, fixed effects for years of education, and an indicator for whether the individual is currently enrolled in school. $\lambda_{time*region}$ are time-by-region fixed effects (where time is the month of the sample, 0 to 132, and region is the Census region).¹⁹ $\delta_{MSA} * f(time)_t$ are MSA-specific time trends, using a linear function of time. BTB is equal to 1 if any BTB policy (affecting government employers and possibly government contractors and/or private firms) is in effect in the individual's MSA. Standard errors are clustered by state. The coefficients of interest, β_1,β_2 , and β_3 , tell us the effect that a BTB policy has on the probability that a white, black, or Hispanic man is employed,

¹⁹Using Census division instead of region yields nearly identical results but is far more computationally intensive.

respectively.

Our preferred specification fully interacts all of the control variables with race. This is equivalent to running the regressions separately by race. Allowing this additional flexibility (where the effect of all controls can vary with race) reduces our statistical power and often has little effect on the estimates. However, for some subgroups it makes a difference. We view this fully-interacted specification as the most conservative approach. For the sake of transparency we will show how the main results change as each set of controls is added.

For each 25- to 34-year-old man in our sample, the full set of controls adjusts for: the average employment probability for men of the same race/ethnicity within his MSA, the employment trend for that race/ethnicity group in his MSA, monthly region-specific employment shocks (such as the housing crash), and his individual characteristics. Any remaining variation in his likelihood of employment would come from idiosyncratic, individual-level factors (for instance, an illness or a fight with a supervisor), or MSA-specific shocks that don't affect nearby MSAs – such as adoption of a BTB policy. Our identifying assumption is that the adoption and timing of BTB policies are exogenous to other interventions or local job market changes that might affect employment, so that – in the absence of BTB – employment probabilities would evolve similarly to those in nearby MSAs without the policy. The most likely threat to identification is that BTB policies were voluntarily adopted by areas that were motivated to help ex-offenders find jobs. The timing of these policies likely coincides with new, local interest in hiring those with criminal records. This should bias our estimated effects upwards, toward finding positive effects on young, low-skilled, black and Hispanic men.

5 Results

Figure 2 shows a local linear graph of the residuals from equation 1, for young, low-skilled black men. Time is recentered so that 0 is the effective date of a jurisdiction's BTB policy. For places without BTB, we recenter using the average effective date – October 2010.²⁰ (Note that we do not

 $^{^{20}}$ To allow sufficient time on either side of the threshold in the graph, we use only jurisdictions where at least 18 months of data were available before and after the date of the policy change. This excludes approximately 20% of our sample, as a large number of jurisdictions adopted BTB in 2013 and 2014. However, the full sample is included in all regressions.

recenter the data in our regression analyses below.) Based on the pre-BTB period, the identifying assumption that BTB and non-BTB jurisdictions would evolve similarly in the absence of BTB – that is, that the treatment and control groups exhibit parallel trends – looks reasonable: the two lines follow each other closely before the date-zero threshold. After that date, however, the lines quickly diverge, with employment outcomes worsening in BTB-adopting places and improving slightly elsewhere. When we consider individuals who live in non-BTB places as a counterfactual for those who live in BTB-adopting places, it appears that BTB dramatically hurt employment outcomes for this group.

Figures 3 and 4 show equivalent graphs for Hispanic and white men, respectively. BTB appears to have a negative effect on Hispanic men, though the pre-trends for BTB and non-BTB areas are not as similar as they were for black men. That said, residuals hover around zero for both sets of jurisdictions before the policy change. They then fall for individuals treated by BTB, while they increase for those living in non-BTB locations. There is no apparent effect on white men.

While this visual evidence is reassuring, we also formally test for differences in pre-period trends as follows: for each race/ethnicity group, we regress the residuals from the pre-period on (1) an indicator for whether the place ever adopted BTB, (2) a linear time trend, and (3) the interaction of the two. The interaction term indicates whether the pre-period trends differ for BTB and non-BTB places. Appendix Table A-3 shows that the differences are near-zero and statistically insignificant for all three groups. This provided evidence that, conditional on the fixed effects and trends included in our preferred specification, non-BTB places were a good counterfactual for the BTB-adopting MSAs during the pre-period. This gives us confidence that they should continue to be good counterfactuals during the post-period.

To consider the outcomes from these graphs more rigorously, Table 4 presents our main results for men ages 25-34 with no college degree. We consider the effect of BTB for each race subgroup (white, black, Hispanic). Each column adds control variables from equation 1 and/or restricts the sample of analysis.

Column 1 shows the effects of BTB in the full sample, controlling only for MSA fixed effects. With no additional information about the individual or the time period, it appears that BTB reduces the probability that low-skilled white men are employed by statistically-significant 5.0 percentage points (p < 0.01). This effect is larger for black men and slightly smaller for Hispanic men.

Column 2 adds detailed information about the individual, including age fixed effects, fixed effects for precise years of education, and whether they are currently enrolled in school. This reduces the magnitude of the above effects slightly, but qualitatively they are very similar.

Column 3 begins to add information about labor market trends, with time-by-region fixed effects; time is the month of the sample and region is the Census region. As expected, controlling flexibly for labor market shocks is important, as our sample period (2004 through 2014) includes the Great Recession. Many BTB policies are implemented at the state-level, so we cannot control for monthspecific state-level shocks. However, most of the non-BTB labor market shocks we are worried about, such as the housing crash, affected MSAs throughout the Census region. These fixed effects should absorb that type of variation.²¹

Controlling for time-by-region fixed effects wipes out the effect of BTB on white men, reducing that coefficient to a small and statistically-insignificant negative 1 percentage point. The effect on black male employment is a statistically significant 3.2 percentage points (p < 0.01). The effect on Hispanic men is also negative 1 percentage point and statistically insignificant.

Column 4 further controls for non-BTB labor market trends with MSA-specific linear time trends. This makes the estimate slightly more precise but has little effect on the estimates.

The effects of the controls and time trends might vary with race – for instance, the employment trend for black men in a particular MSA might be different from the trend for white men. Column 5 presents the results of a fully-interacted model, where the effects of all of the control variables in equation 1 are allowed to differ across race/ethnicity groups (white, black, and Hispanic). This reduces our statistical power substantially, but is the most conservative approach to isolating the effect of BTB. It is equivalent to running the regressions separately by race. Based on these estimates, BTB reduced employment for black men by a statistically-significant 3.4 percentage points (5.1%), and for Hispanic men by a marginally-significant 2.3 percentage points (2.9%). This is our preferred specification.

One concern about using non-BTB jurisdictions as controls is that they tend to be less urban and have smaller black populations than places that adopt BTB. Even after controlling for pre-existing

²¹Using (smaller) Census divisions instead of Census regions yields nearly identical results.

trends, they might not be good counterfactuals for the places likely to adopt BTB. Columns 6 and 7 restrict the sample to places that are similar to BTB-adopting labor markets.

Column 6 considers only individuals living in MSAs – that is, it excludes individuals living in more rural areas. (In our dataset, those individuals could still have been affected by state-level policies.) Since BTB-adopting jurisdictions tend to be more urban, perhaps it makes the most sense to compare them only with similarly-urban places. Under this restriction, we lose about one-third of our original sample. When we limit attention to individuals in or near cities, we have less statistical power but the effect on black and Hispanic men is similar to before: BTB reduces employment for black men by 2.9 percentage points (p < 0.05) and by 2.3 percentage points (p < 0.10) for Hispanic men.

Column 7 restricts attention to only jurisdictions that adopted BTB by December 2014. If some types of places are more motivated to help ex-offenders or reduce racial disparities in employment, and thus to adopt BTB, labor market trends might be fundamentally different than they are in other places. This compares apples with apples, so to speak – we consider only individuals who live in places that eventually adopt BTB, and rely on variation in the timing of policy adoption to identify BTB's effect. This reduces our sample to under half of what it was originally, so we again lose statistical power, but the magnitudes of the estimates are very similar to those in column 5. BTB has no significant effect on white male employment, but reduces the probability of employment by 3.1 percentage points for black men (p < 0.05), and by 2.0 percentage points for Hispanic men (not statistically significant).

Some readers might be concerned that our specification does not control sufficiently for local labor market shocks. To address this, column 8 adds a time-varying control for the MSA unemployment rate. Since this only applies to individuals living in an MSA, we restrict the sample to that population, as in column 6. Controlling for unemployment when our outcome variable is the probability of employment raises obvious endogeneity concerns – if BTB reduces local employment rate overall (due to the increase in expected hiring costs), then controlling for the unemployment rate could mask that effect. However, if BTB simply shifts employment from one group to another, leaving the overall unemployment rate unchanged, then controlling for the local unemployment rate might not make a difference. As column 8 shows, controlling for MSA-level unemployment has little

effect on our estimates. This suggests two things: (1) our estimates are not the result of local labor market shocks unrelated to BTB, and (2) at least in the short run, BTB shifts employment from one group to another rather than reducing the total number of people employed.

Overall, these results tell the same story as the graphs described above. It is reassuring to find such similar effects across most specifications and samples. In particular, our robustness samples including only metro areas or only BTB-adopting places show extremely similar effects. The fullyinteracted model is required to detect BTB's effect on Hispanic men, but that effect is also robust to different sample definitions. We see no significant effect of BTB on white men without college degrees in this age group.

5.1 Differential effects by region

Given differences in racial composition and labor markets across the country, we might expect BTB to have different effects in different places. Table 5 separately considers the effects of BTB by Census region. To simplify presentation, we show the results separately by race, so the coefficients are comparable to the total effects (by race) in the fully-interacted model from column 5 above.

We see that young, low-skilled white men are not affected by BTB anywhere. However, the employment probabilities of their black peers are significantly reduced in three regions: the Northeast (7.4%), the Midwest (7.5%), and the West (8.8%). The negative effect on black men is much smaller (2.3%) and not statistically significant in the South, where a larger share of the population is black.²²

Similarly, we see evidence of differential effects for Hispanic men, though limited statistical power means that none of the coefficients are statistically significant. The coefficients are negative across all four regions, but are much larger in the Northeast (3.5%), the Midwest (5.7%), and the South (3.6%). The estimated effect for Hispanic men living in the West – where a larger share of the population is Hispanic – is near zero.²³

These results suggest that the larger the black or Hispanic population, the less likely employers

 $^{^{22}}$ Based on 2010 Cenus data, 19% of the population in the South is black, compared with 12% in the Northeast, 10% in the Midwest, and 5% in the West (Rastogi et al., 2011).

²³Based on 2010 Cenus data, 29% of the population in the West is Hispanic, compared with 13% in the Northeast, 7% in the Midwest, and 16% in the South (Ennis et al., 2011).

are to use race/ethnicity as a proxy for criminality.

5.2 BTB in weak vs. strong labor markets

Employers might be quicker to exclude large categories of job applicants – such as those with criminal records, or young black men – when they have many applicants to choose from than when it is relatively difficult to find qualified employees. We therefore might expect a policy like BTB to have larger negative effects on the employment of young, low-skilled black and Hispanic men when the unemployment rate is high than when it is low. Table 6 adds terms that allow the effect of BTB to vary with the national unemployment rate. (We use the national unemployment rate rather than state or local unemployment rates to limit concerns about reverse causality.) Effects are shown separately by race (equivalent to the total effects estimated in column 5 in Table 4).

Columns 1 and 2 show the effect on white men, including linear and quadratic functions of the unemployment rate, respectively. The total effects of BTB are calculated at 5%, 6%, 7%, 8% and 9% national unemployment. (During this period, the unemployment rate ranged from 4.4% to 10.0%.) The effect of the policy on white men is slightly positive when unemployment is low, and slightly negative when unemployment is high, but at all unemployment rates the effect is near-zero and statistically insignificant.

Columns 3 and 4 show the effect on black men. Again the effect of BTB is more negative when unemployment is high, but now the estimated total effects are relatively large and negative even at low unemployment. The negative total effect becomes statistically significant at 7% or 8% unemployment, and at 9% unemployment the total effect of BTB on black men is over 3.6 percentage points and statistically significant (p < 0.05).

Columns 5 and 6 show the effect on Hispanic men. The same pattern emerges: the total effect of the policy is more negative as the unemployment rate rises, and that effect becomes statistically significant when unemployment reaches 7% or 8%. With the quadratic term included, the total effect of BTB on Hispanic men is near-zero and statistically insignificant at 5% unemployment, but reaches -3.2% (p < 0.05) at 9% unemployment.

These results confirm that employers are more likely to statistically discriminate when the supply of labor greatly exceeds the demand for it. They also suggest that BTB policies may have worsened the effect of the recent recession for these disadvantaged groups.

5.3 Substitution to other groups

BTB has the predicted effects on the group most directly affected by the policy, decreasing the probability of employment for young, low-skilled black and Hispanic men. Other groups might also be affected, as the beneficiaries of statistical discrimination. In particular, we might expect employers to prefer groups that are less likely to include recently-incarcerated offenders, such as older applicants, those with college degrees, women, and/or white applicants. However, it is also possible that increasing the asymmetric information problem in this labor market could reduce total employment.

Table 7 presents the results of a fully-interacted model (equivalent to column 5 in Table 4 above) for other demographic groups.

Column 1 considers men ages 25-34 with college degrees. This group is far less likely to include individuals with criminal records, so employers might prefer to interview them after BTB removes criminal history information from job applications. However, college-educated men are unlikely to be interested in low-skilled jobs. We see that the effect of BTB on employment in this group is very small and statistically insignificant.

Column 2 considers the effect of BTB on older working-age men, ages 35-64, with no high school diploma. These men are still more likely to have a criminal record, but are much less likely than younger men to have been recently incarcerated and/or to still be actively engaged in criminal behavior or associating with people who are. A previous criminal conviction might therefore be less worrisome for a potential employer. We see that this is the case with respect to black men: on average, BTB increases their employment by 4.3 percentage points (9.4%), though this effect is not statistically significant. However, the effect on Hispanic men is negative and about as large as before: 2.8 percentage points (3.9%).

Column 3 considers the effect for older men (age 35-64) with no college degree – our preferred definition of "low-skilled". Here we see that BTB increases black male employment by a statistically significant 2.8 percentage points (4.3%). The effect on Hispanic men is also positive (1.5 percentage points, which is 1.9% of the pre-BTB baseline) but not statistically significant. This suggests that

employers are weighting age more heavily when they consider job applicants, substituting away from young black and Hispanic men and toward older black (and possibly Hispanic) men of the same educational level, to avoid interviewing individuals with recent convictions.

Column 4 considers the effect on older men with a college degree. As for highly-educated younger men, we see no effects here.

Column 5 considers young (age 25-34) women with no high school diploma. Women are less likely than men to have a criminal record, and particularly less likely to commit violent crime. If violent behavior is a primary concern for employers, we might see substitution into this group. However, female employment might also respond to male partners' inability to find a job, so an increase in employment might tell us more about intrahousehold responses than employers' preference. There is some evidence that white women are more likely to work when BTB is in effect (employment increases by 1.2 percentage points, 2.6% of the baseline), and that black women work less (employment decreases by 2.9 percentage points, 6.4% of the baseline), but neither effect is statistically significant.

Column 6 considers young women with no college degree. There are no significant effects here, although Hispanic women in this group seem to benefit slightly, on average.

Column 7 considers young women with a college degree. BTB increases employment by a statistically significant 3.2 percentage points (3.9%) for black women in this group. Given that college-educated women and men without college degrees are likely working in different labor markets, this probably reflects intrahousehold substitution of labor rather than employers' preference for hiring women due to BTB.

5.4 Persistence of effects over time

It's possible that BTB increases the expected cost of hiring low-skilled black and Hispanic men such that the policy permanently lowers employment for these groups. Alternatively, we might expect BTB to have a temporary effect if employers and workers eventually adapt to the policy and return to the pre-BTB equilibrium. For instance, employers might figure out new ways to screen job applicants, and workers might learn new ways to signal their job-readiness to employers.

Table 8 shows the cumulative effects of BTB on employment over time, for young, low-skilled

white, black, and Hispanic men, respectively. The coefficients show the effect of BTB during the first year, the second year, the third year, and four or more years after the policy went into effect.

Across all years, BTB's effect on white men is near-zero and statistically insignificant. However, BTB's effect on black men is large and grows over time. BTB reduces employment for black men by 2.7 percentage points (not statistically significant) in the first year, 5.1 percentage points (p < 0.01) in the second year, 4.1 percentage points (p < 0.10) in the third year, 8.4 percentage points (p < 0.01) in the fourth year, and an average of 7.7 percentage points (p < 0.05) in the fifth and later years. This suggests that BTB has a permanent effect on employment for black men.

Effects on Hispanic men tell a different story: BTB reduces employment for this group by 1.6 percentage points (not statistically significant) in the first year after the policy goes into effect, by 3.0 percentage points (p < 0.10) in the second year, and by 2.6 percentage points (not statistically significant) in the third year. However, after the third year the effect declines to near-zero. It appears that young Hispanic men adapt to the policy over time, perhaps by using their networks to find jobs and signal their job-readiness to employers. This is consistent with previous evidence that labor market networks play a particularly important role in hiring for low-skilled Hispanics (Hellerstein et al., 2011).

5.5 Effects by type of law

As discussed in Section 2, BTB laws take different forms in different places. So far we have considered the effects of having any BTB policy – whether it applies to government jobs only or also to private firms (with or without government contracts). Thirteen percent of MSAs are affected by some form of private BTB law by the end of 2014.²⁴ The places that passed such laws are listed in Table 3, and include Compton, CA, (contract, July 2011), San Francisco (contract and private, April 2014), the state of Illinois (contract and private, July 2014), Baltimore, MD (contract and private, April 2014), and Cambridge, MA (contract, January 2008). Most other places did not, including locations very similar to those that did. There is not yet enough variation to tease apart the effects of contract and private BTB laws, but we have sufficient power to consider whether adding at least private firms with government contracts has an effect beyond that of having only a public BTB law.

²⁴Thirteen percent adopted contract BTB laws during this period, while 11 percent also adopted private BTB laws.

Table 9 shows differential effects by law types, separately by race/ethnicity. For black and Hispanic men, adding private firms has no significant effect beyond the effect of a public BTB law: the coefficients on the interaction term are negative, but small (albeit with large standard errors). However, for white men, adding private firms has a large and statistically significant effect on employment: it increases employment by 3.7 percentage points (4.5%). This is consistent with the findings in Agan and Starr (2016), which focused on the effects of private BTB laws. In that study, black men were called back at rates in between the pre-BTB rates for those with and without criminal records. However, after BTB white men were called back at rates slightly higher than the pre-BTB rate for non-offenders: that is, that study found that BTB helped white ex-offenders (and possibly also white non-offenders) get more callbacks. However, it is not clear if those men (particularly white men with records) would have gotten jobs once the employer ran a background check at the end of the hiring process. Indeed, contract and private BTB laws do appear to increase employment for white men.

6 Robustness

6.1 Effects on young men without a high school diploma

In the above analyses, we define "low-skilled" as having no college degree, for two reasons: (1) this group includes the vast majority of ex-offenders, and (2) it provides sufficient sample size to draw sound conclusions. However, we expect effects to be larger in magnitude for the subset of that population with less education.

Table A-4 presents the main results for those without a high school diploma or GED. The effects of BTB on black and Hispanic men are indeed larger in magnitude, but imprecisely estimated due to the relatively small sample. Our preferred specification (column 5) estimates that BTB reduces employment for black men by 14.9 percentage points (33% of the baseline); the 95% confidence interval suggests that this negative effect could range from 7.2 percentage points (16%) to 22.5 percentage points (50%). For Hispanic men we estimate that BTB reduces employment by 9.5 percentage points (13%); the 95% confidence interval suggests this negative effect could range from 4.2 percentage points (5.8%) to 14.8 percentage points (20%). We also find suggestive evidence that BTB has a positive effect on white men with no high school diploma. On average, white men in this group are 3.9 percentage points (5.6%) more likely to be employed after BTB than before, but this effect is not statistically significant.

6.2 Effects of individual states on the main estimates

The implementation and effects of BTB could vary across states, and particular states might be driving our main results. Looking at effects by region provides some evidence on this issue, but we now focus on the effects of individual states. Tables A-5 and A-6 reproduce column 5 from Table 4, dropping each state, in turn. Across the board, the results are qualitatively consistent with our main results, but there are some states that have particularly strong effects on the estimates. Excluding Colorado or New Jersey, for instance, increases the magnitude and statistical significance of the effect on Hispanic men, suggesting those states are outliers. Dropping Virginia increases the magnitude and statistical significance of the effect on black men, while dropping DC or South Carolina reduces the magnitude of that effect slightly.

6.3 Effects by type of job

BTB laws initially target government jobs, but likely affect both public and private jobs. Workers can move between sectors and might target their job-search efforts based on where they expect they are most welcome. If ex-offenders think they're more likely to get a government job, they might reduce their efforts to find available jobs in the private sector, and might wind up without any job as a result. (This would be consistent with anecdotal evidence that, by preventing employers from screening job applicants efficiently, both employers and applicants waste their time pursuing inappropriate matches.) In addition, the public pressure that resulted in a public BTB law could extend to local firms, prompting private employers to adopt what is viewed as a hiring 'best practice' (not asking about an applicant's criminal record on the job application).

We consider the differential effects of BTB by employer type to see which sector is driving the overall declines in black and Hispanic employment. Table A-7 shows the results specifically for the probability that the survey respondent reports working at a public sector job. There is no significant effect on public sector employment for white or Hispanic men, but black men do see a drop in public sector employment after BTB goes into effect. Based on this estimate, about half of the overall effect on black men comes from a reduction in public sector jobs.

6.4 Effects on migration

By using individual-level data, we avoid major concerns about the composition of local populations changing over time, because we can control for observable characteristics. However, it is possible that the composition of the population is changing in ways that are unobservable. In particular, it's possible that BTB induces people with criminal records to move to places that adopt BTB, because they think the policy will improve their job opportunities. If unemployed black men with criminal records – who are otherwise identical to the other black men in the area – are disproportionately likely to move into a BTB area, it could look like the probability of employment for black men is falling when in fact the composition of residents is changing to include more black men who are difficult to employ. This would bias our estimates toward finding a negative effect of the policy on employment for this group. On the other hand, if any black men moving in are the most motivated to find a job (which, given the social and financial costs of moving, is highly likely), then the population of BTB places would shift to be more motivated on average. This would bias our estimates toward finding a positive effect of BTB on employment. The same positive bias would result if black men with criminal records move into a BTB county *after* finding a job there, rather than in search of a job.

To test for migration across labor markets in response to BTB, we utilize the March CPS supplements, which contain questions on migration. We focus on three outcomes based on the migration questions: moving within county, moving within state but across counties, and moving across states. We test whether BTB affects the likelihood that an individual experienced any of these types of moves within the previous year. We examine migration outcomes for low-skilled individuals, separately for all men, black men, young men, and young black men. The point estimates are reported in Table A-8, and are discussed in more detail in Doleac and Hansen (2017).

We find no evidence that BTB adoption is associated with differential intra-state or inter-state migration rates for these demographic groups. Since local labor markets are defined at the MSA level (and MSAs span multiple counties), these results imply that the compositions of local labor markets are *not* changing as a result of BTB. The only statistically significant and economically meaningful estimate emerges for intra-county moves for young, low-skilled black men: this group is *less* likely to move within-county after BTB is implemented. While not affecting the composition of MSAs, this effect is consistent with reduced labor market options for young black men: these men may have less need to move across the county to be closer to a new employer.

7 Discussion

"Ban the box" has arisen as a popular policy aimed at helping ex-offenders find jobs, with a related goal of decreasing racial disparities in employment. However, BTB does not address employers' concerns about hiring those with criminal records, and so could increase discrimination against groups that are more likely to include recently-incarcerated ex-offenders – particularly young, lowskilled black and Hispanic men.

In this paper, we exploit the variation in adoption and timing of state and local BTB policies to estimate BTB's effects on employment for these groups. We find that BTB reduces the probability of employment for young black men without a college degree by 3.4 percentage points (5.1%), and for young Hispanic men without a college degree by 2.3 percentage points (2.9%). The effect on black men is particularly robust across different specifications and samples.

These effect sizes may seem large but they are consistent with those found in related studies. Holzer et al. (2006) found that the last hire was 37% more likely to be a black man when firms conducted criminal background checks, while Bartik and Nelson (2016) found that banning credit history checks reduced the likelihood of finding a job by 7-16% for black job-seekers. Given relatively high turnover rates in the low-skilled labor market, it does not take long for increases or decreases in hiring rates to result in a large change in employment.²⁵ For instance, in a similar context Wozniak (2015) found that allowing drug testing by employers increased employment for low-skilled black men by 7-30%.

²⁵Based on data from the Job Openings and Labor Turnover Survey (JOLTS), industries with high proportions of low-skilled jobs, such as construction, retail trade, and hospitality services, have monthly separations hovering around 5-6% of total employment. (Data are unavailable by age and skill level, so this likely underestimates the degree of turnover for our population of interest.) If we conservatively assume (1) a 5.5% monthly separation rate for the jobs held by young, low-skilled black men, and (2) that BTB reduces hiring rates for this population by 7%, then we would expect a 5% reduction in employment within 14 months. This is in line with our results from Table 8.

In light of these other studies and estimated turnover rates, our estimates are plausible and may actually be somewhat small. Indeed, our effects are likely biased upwards (toward finding positive effects of BTB) for two reasons: (1) Jurisdictions that adopt BTB are typically more motivated to help ex-offenders find jobs, and this motivation alone should increase employment for those with criminal records. (2) The CPS excludes individuals who are incarcerated, so if some of the men who are unemployed as a result of BTB commit crime and are sent to prison, they will not be included in our sample.

Most work on statistical discrimination posits that employers will infer applicants' productivity correctly, on average, and so small differences in criminal histories across black and white men should have smaller effects on employment outcomes than larger differences would. In this framework, where employers think of productivity as a continuous measure, and the likelihood of hiring an applicant (or the wage someone is paid) increases with their expected productivity, this might be correct. However, if employers are comparing multiple applicants for a single job opening, even small differences in expected productivity across racial groups could have large effects on hiring. If a criminal record is correlated with low productivity, and black men are more likely to have a criminal record, then when faced with identical applications from a black man and a white man, an employer will assign lower expected productivity to the black applicant every time, and always choose the white applicant. This decision-making process – where applicants are not judged in a vacuum based on their expected productivity but compared with other applicants – can explain the apparently large effects of policies like BTB on hiring and employment, even when real-world differences in criminal histories are relatively small.²⁶

This is the first paper to consider the effects of BTB on the employment of young, low-skilled black and Hispanic men, but our findings are consistent with theory and other research about statistical discrimination in employment. We find evidence that BTB has unintentionally done more harm than good when it comes to helping disadvantaged job-seekers find jobs. More research on the dynamics of job application behavior and the differential effects across law types would be helpful in understanding how job applicants and employers respond to this and similar labor market

²⁶The same effect would emerge if employers compare applicants' expected productivity with some threshold cutoff, rather than other applicants.

policies. Understanding how these actors interpret and utilize information in employment decisions can help us design better policies going forward.

Increasing employment rates for ex-offenders is a top policy priority, for good reason, but policymakers cannot simply wish away employers' concerns about hiring those with criminal records. Policies that directly address those concerns – for instance, by providing more information about job applicants with records, or improving the average ex-offender's job-readiness – could have greater benefits without the unintended consequences found here.

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8 Figures and Tables

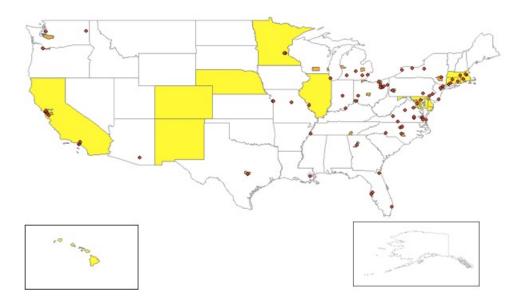


Figure 1: Jurisdictions with BTB policies by December 2014

Jurisdictions with BTB policies are represented by yellow shading (state-level policies), orange shading (county-level policies), and red dots (city-level policies.)

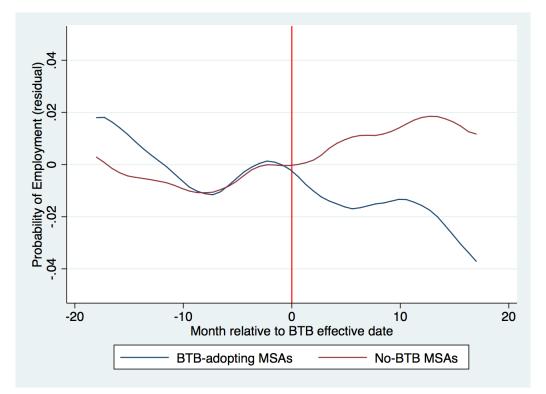
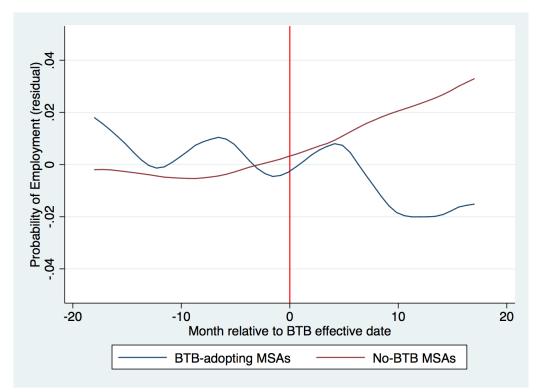


Figure 2: Effect of BTB on probability of employment for black men ages 25-34, no college degree

Data source: CPS 2004-2014. Sample includes black men ages 25-34 who do not have a college degree. To allow at least 18 months of data before and after the effective date, this graph is limited to jurisdictions that implemented BTB between June 2005 and July 2013. The mean of the effective dates applying to this group for BTB-adopting jurisdictions in this window – October 2010 – is used as the "effective date" for the no-BTB jurisdictions.

Figure 3: Effect of BTB on probability of employment for Hispanic men ages 25-34, no college degree



Data source: CPS 2004-2014. Sample includes Hispanic men ages 25-34 who do not have a college degree. To allow at least 18 months of data before and after the effective date, this graph is limited to jurisdictions that implemented BTB between June 2005 and July 2013. The mean of the effective dates applying to this group for BTB-adopting jurisdictions in this window – May 2010 – is used as the "effective date" for the no-BTB jurisdictions.

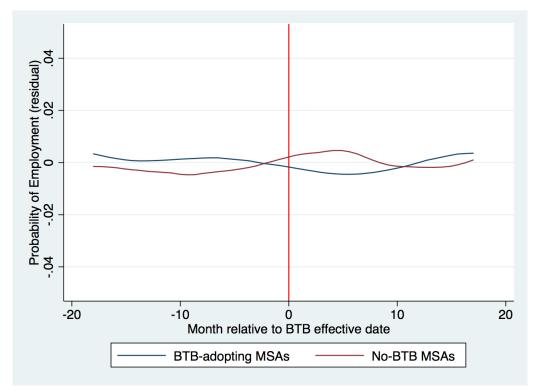


Figure 4: Effect of BTB on probability of employment for white men ages 25-34, no college degree

Data source: CPS 2004-2014. Sample includes white, non-Hispanic men ages 25-34 who do not have a college degree. To allow at least 18 months of data before and after the effective date, this graph is limited to jurisdictions that implemented BTB between June 2005 and July 2013. The mean of the effective dates applying to this group in BTB-adopting jurisdictions in this window – May 2010 – is used as the "effective date" for the no-BTB jurisdictions.

	Men ag	ges 25-34	Men ag	ges 35-64
	Mean	(SD)	Mean	(SD)
BTB	0.1930	(0.3946)	0.1870	(0.3899)
Employed	0.8335	(0.3725)	0.8026	(0.3981)
No HS diploma or GED	0.0769	(0.2665)	0.0847	(0.2784)
No college degree	0.5883	(0.4921)	0.5804	(0.4935)
College degree or more	0.4117	(0.4921)	0.4196	(0.4935)
Enrolled in school	0.0145	(0.1196)	0.0023	(0.0478)
Age	29.492	(2.8835)	48.930	(8.0649)
White	0.7934	(0.4048)	0.8399	(0.3667)
Black	0.0965	(0.2953)	0.0893	(0.2851)
Hispanic	0.1100	(0.3129)	0.0709	(0.2566)
Northeast	0.1881	(0.3908)	0.2154	(0.4111)
Midwest	0.2563	(0.4366)	0.2526	(0.4345)
South	0.3155	(0.4647)	0.3118	(0.4632)
West	0.2401	(0.4271)	0.2202	(0.4144)
Metro area	0.7089	(0.4543)	0.6819	(0.4657)
Ν	85	5,772	2,87	73,182

Table 1: Summary Statistics

Data source: 2004-2014 Current Population Survey.

Table 2: Summary	V Statistics: Men a	ages $25-34$ with no colle	ege degree
	All	Never adopted BTB	Adopted BTB
White Non-Hispanic			
BTB	0.1414(0.3484)	0 (0)	0.3408(0.4740)
Employed	0.8087(0.3933)	0.8110(0.3915)	$0.8055\ (0.3958)$
No HS diploma or GED	0.1094(0.3121)	0.1198(0.3247)	$0.0947 \ (0.2927)$
Enrolled in school	0.0115(0.1068)	0.0099(0.0989)	0.0139(0.1169)
Age	$29.424 \ (2.8935)$	29.433(2.8886)	29.411 (2.9003)
Northeast	0.1883 (0.3910)	$0.1583 \ (0.3651)$	0.2307(0.4213)
Midwest	0.2873(0.4525)	0.2513(0.4338)	0.3380(0.4730)
South	0.2909(0.4542)	$0.3541 \ (0.4782)$	$0.2017 \ (0.4013)$
West	$0.2335\ (0.4231)$	0.2362(0.4248)	$0.2297 \ (0.4206)$
Metro area	$0.6127 \ (0.4871)$	$0.4261 \ (0.4945)$	$0.8760\ (0.3295)$
N	373,237	218,413	154,824
Black Non-Hispanic			
BTB	$0.2006 \ (0.4005)$	0 (0)	$0.3481 \ (0.4764)$
Employed	$0.6564 \ (0.4749)$	0.6588(0.4741)	0.6547(0.4755)
No HS diploma or GED	0.1498(0.3569)	0.1659(0.3720)	0.1380(0.3449)
Enrolled in school	0.0132(0.1143)	0.0122(0.1097)	$0.0140 \ (0.1175)$
Age	29.371(2.9194)	29.419(2.8761)	29.336(2.9504)
Northeast	0.1228(0.3283)	0.0405(0.1971)	0.1834(0.3870)
Midwest	0.1898(0.3921)	$0.0930 \ (0.2905)$	0.2609(0.4392)
South	$0.5916\ (0.4915)$	0.7943(0.4042)	$0.4427 \ (0.4967)$
West	$0.0957 \ (0.2942)$	$0.0722 \ (0.2587)$	$0.1130\ (0.3166)$
Metro area	0.8174(0.3864)	$0.6110\ (0.4875)$	$0.9690\ (0.1733)$
N	59,872	25,363	34,509
Hispanic			
BTB	0.2687(0.4433)	0 (0)	0.4435(0.4968)
Employed	$0.7921 \ (0.4058)$	0.8138(0.3893)	0.7779(0.4156)
No HS diploma or GED	0.2283(0.4198)	$0.2481 \ (0.4319)$	0.2154(0.4111)
Enrolled in school	0.0149(0.1211)	$0.0141 \ (0.1178)$	$0.0154 \ (0.1232)$
Age	29.303(2.8739)	29.251 (2.8762)	29.338(2.8719)
Northeast	0.1376(0.3445)	0.0394(0.1946)	0.2014(0.4011)
Midwest	0.1065(0.3084)	$0.0856\ (0.2798)$	0.1200(0.3250)
South	0.2983(0.4575)	0.5669(0.4955)	0.1236(0.3291)
West	0.4577(0.4982)	0.3081 (0.4617)	0.5550(0.4970)
Metro area	0.8394(0.3672)	0.7058(0.4557)	0.9262(0.2614)
Ν	70,310	27,710	42,600
Data gourge: 2004 2014 C	unnerst Denulation	Current Standard anno	na in namentheses

Table 2: Summary Statistics: Men ages 25-34 with no college degree

Data source: 2004-2014 Current Population Survey. Standard errors in parentheses.

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Table 3: Ban the Box policies implemented by December 2014

State Jurisdiction Law Type Start Date Detroit Public September 13, 2010 Detroit Contract June 1, 2012 East Lansing Public April 15, 2014 Public Genesee County June 1, 2014 Kalamazoo Public January 1, 2010 Muskegon Public January 12, 2012 Minnesota Public January 1, 2009 State State Contract January 1, 2009 May 13, 2013 State Private December 1, 2006 Minneapolis Public December 5, 2006 St. Paul Public Missouri Columbia Public December 1, 2014 Columbia Contract December 1, 2014 Columbia Private December 1, 2014 Kansas City Public April 4, 2013 St. Louis Public October 1, 2014 Nebraska Public April 16, 2014 State New Jersey Atlantic City Public December 23, 2011 Atlantic City Contact December 23, 2011 Newark Public September 19, 2012 Newark Contract September 19, 2012 Newark Private September 19, 2012 New Mexico State Public March 8, 2010 New York New York City Public October 3, 2011 New York City Contract October 3, 2011 Buffalo Public June 11, 2013 Buffalo June 11, 2013 Contract Buffalo Private June 11, 2013 Rochester May 20, 2014 Public May 20, 2014 Rochester Contract Rochester May 20, 2014 Private Woodstock Public November 18, 2014 Yonkers Public November 1, 2014 North Carolina Carrboro Public October 16, 2012 Charlotte Public February 28, 2014 September 6, 2011 Cumberland County Public February 1, 2011 Durham Public Durham County Public October 1, 2012 Spring Lake Public June 25, 2012 Ohio Alliance Public December 1, 2014 Akron Public October 29, 2013 Cincinnati Public August 1, 2010 Cleveland September 26, 2011 Public Canton Public May 15, 2013 Cuyahoga County Public September 30, 2012 Franklin County Public June 19, 2012 Public Hamilton County March 1, 2012 Lucas County Public October 29, 2013 Massillon Public January 3, 2014 Stark County Public May 1, 2013 Summit County Public September 1, 2012 Youngstown Public March 19, 2014 Oregon Multnomah County Public October 10, 2007 Portland Public July 9, 2014 Allegheny County November 24, 2014 Pennsylvania Public

Table 3:	(continued)
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Public

October 1, 2014

Lancaster

State	Jurisdiction	Law Type	Start Date
	Philadelphia	Public	June 29, 2011
	Philadelphia	Contract	June 29, 2011
	Philadelphia	Private	June 29, 2011
	Pittsburgh	Public	December 17, 2012
Rhode Island	State	Public	July 15, 2013
	State	Contract	July 15, 2013
	State	Private	July 15, 2013
	Providence	Public	April 1, 2009
Tennessee	Memphis	Public	July 9, 2010
	Hamilton County	Public	January 1, 2012
Texas	Austin	Public	October 16, 2008
	Travis County	Public	April 15, 2008
Virginia	Newport News	Public	October 1, 2012
	Richmond	Public	March 25, 2013
	Portsmouth	Public	April 1, 2013
	Norfolk	Public	July 23, 2013
	Petersburg	Public	September 3, 2013
	Alexandria	Public	March 19, 2014
	Arlington County	Public	November 3, 2014
	Charlottesville	Public	March 1, 2014
	Danville	Public	June 3, 2014
	Fredericksburg	Public	January 1, 2014
	Virginia Beach	Public	November 1, 2013
Washington	Seattle	Public	April 24, 2009
-	Seattle	Contract	January 1, 2013
	Spokane	Public	July 31, 2014
	Pierce County	Public	January 1, 2012
Wisconsin	Dane County	Public	February 1, 2014
	Milwaukee	Public	October 7, 2011

Table 3: (continued)

Source: Rodriguez and Avery (2016) and local legislation.

Laule 4.								
	(1)	(2)	(3)	(4)	(5)	(9)	(2)	(8)
White * BTB	-0.0501^{***}	-0.0420^{***}	-0.0100	-0.0072	-0.0028	-0.0091	-0.0048	-0.0088
	(0.0088)	(0.0089)	(0.0073)	(0.0058)	(0.0061)	(0.0064)	(0.0077)	(0.0061)
Black * BTB	-0.0716^{***}	-0.0605***	-0.0320^{***}	-0.0296^{***}	-0.0342^{**}	-0.0291^{**}	-0.0311^{**}	-0.0306^{**}
	(0.0113)	(0.0118)	(0.0114)	(0.0103)	(0.0149)	(0.0143)	(0.0136)	(0.0145)
Hispanic * BTB	-0.0489 ***	-0.0476^{***}	-0.0120	-0.0046	-0.0234^{*}	-0.0228^{*}	-0.0196	-0.0229*
	(0.0088)	(0.0097)	(0.0113)	(0.0126)	(0.0130)	(0.0120)	(0.0147)	(0.0119)
Ν	503,419	503,419	503,419	503, 419	503,419	336,641	231,933	336,641
Pre-BTB baseline								
White	0.8219	0.8219	0.8219	0.8219	0.8219	0.8226	0.8219	0.8226
Black	0.6770	0.6770	0.6770	0.6770	0.6770	0.6770	0.6770	0.6770
Hispanic	0.7994	0.7994	0.7994	0.7994	0.7994	0.7985	0.7994	0.7985
Controls:					Х			
MSA FEs	Х	Х	Х	Х	X	X	X	Х
Demographics		Х	Х	Х	X	X	X	Х
Time * Region FEs			X	X	Х	X	Х	Х
MSA-specific trends				X	Х	X	Х	Х
Fully-interacted with race					Χ	Χ	X	Х
MSA unemployment								Х
Sample:								
Full sample	Х	Х	Х	Х	Х			
MSAs only						X		Χ
BTB-adopting only							X	

p < 0.10, ** $p < 0.05$, *** $p < 0.01$. Data source: CPS 2004-2014. Coefficients show the effect (in perpendicular to the probability of employment.

	White	Black	Hispanic
Northeast			
BTB	-0.0163	-0.0476^{**}	-0.0266
	(0.0096)	(0.0185)	(0.0170)
Ν	70,298	$7,\!355$	9,673
Pre-BTB baseline	0.8193	0.6447	0.7605
Midwest			
BTB	0.0140	-0.0492**	-0.0464
	(0.0081)	(0.0195)	(0.0271)
N	107,215	11,364	7,485
Pre-BTB baseline	0.8192	0.6390	0.8170
South			
BTB	0.0098	-0.0164	-0.0302
	(0.0144)	(0.0302)	(0.0368)
N	108,565	35,423	20,974
Pre-BTB baseline	0.8328	0.7094	0.8357
West			
BTB	-0.0184	-0.0598**	-0.0086
	(0.0104)	(0.0245)	(0.0243)
N	87,159	5,730	32,178
Pre-BTB baseline	0.8171	0.6780	0.7978
Controls:			
MSA FEs	Х	Х	Х
Demographics	Х	Х	Х
Time FEs	Х	Х	Х
MSA-specific trends	Х	Х	Х

Table 5: Effects on Employment for Men ages 25-34 with no college degree

* p < 0.10, ** p < $\overline{0.05}$, *** p < 0.01. Data source: CPS 2004-2014. Coefficients show the effect (in percentage points) of BTB on the probability of employment.

	<u> </u>	nite	<u> </u>	ack	<u> </u>	panic
	(1)	(2)	(3)	(4)	(5)	(6)
BTB	0.0213	0.0456	-0.0170	0.1194	0.0054	0.3147*
	(0.0226)	(0.0896)	(0.0540)	(0.2927)	(0.0355)	(0.1873)
BTB * Unemp. Rate	-0.0031	-0.0100	-0.0022	-0.0407	-0.0036	-0.0934
	(0.0030)	(0.0268)	(0.0064)	(0.0831)	(0.0043)	(0.0562)
BTB * (Unemp. Rate) ²		0.0005		0.0026		0.0061
		(0.0019)		(0.0056)		(0.0039)
Total effect of BTB:						
5% Unemployment	0.0058	0.0081	-0.0280	-0.0191	-0.0126	0.0002
6% Unemployment	0.0027	0.0036	-0.0302	-0.0312	-0.0162	-0.0261
7% Unemployment	-0.0004	0.0001	-0.0324^{*}	-0.0381	-0.0198	-0.0402^{*}
8% Unemployment	-0.0035	-0.0024	-0.0346**	-0.0398^{*}	-0.0234^{*}	-0.0421^{**}
9% Unemployment	-0.0066	-0.0039	-0.0368**	-0.0363**	-0.0270^{*}	-0.0318^{**}
N	373,237	373,237	59,872	59,872	70,310	70,310
Pre-BTB baseline	0.8219	0.8219	0.6770	0.6770	0.7994	0.7994
Controls:						
MSA FEs	Х	Х	Х	Х	Х	Х
Demographics	Х	Х	Х	Х	Х	Х
Time * Region FEs	Х	Х	Х	Х	Х	Х
MSA-specific trends	Х	Х	Х	Х	Х	Х

Table 6: Effects on Employment for Men ages 25-34 with no college degree

* p < 0.10, ** p < 0.05, *** p < 0.01. Data source: CPS 2004-2014. Coefficients show the effect (in percentage points) of BTB on the probability of employment.

		Men	en			VV OTHER	
	Ages 25-34		Ages 35-64			Ages 25-34	
	College	No HS	No college	College	N_{O} HS	No college	College
	degree	diploma	degree	degree	diploma	degree	degree
White * BTB	0.0044	0.0141	0.0003	0.0045	0.0115	0.0006	0.0005
	(0.0043)	(0.0140)	(0.0043)	(0.0032)	(0.0291)	(0.0092)	(0.0045)
Black * BTB	0.0078	0.0428	0.0280^{***}	0.0032	-0.0284	0.0017	0.0315^{**}
	(0.0159)	(0.0282)	(0.0092)	(0.0144)	(0.0303)	(0.0118)	(0.0150)
Hispanic * BTB	-0.0018	-0.0280^{**}	0.0148	0.0104	0.0030	0.0192	0.0027
	(0.0155)	(0.0130)	(0.0093)	(0.0101)	(0.0401)	(0.0220)	(0.0198)
N	352, 353	243,267	1,667,573	1,205,609	60,110	477,531	458,692
Pre-BTB baseline:							
White	0.9052	0.6184	0.7875	0.8862	0.4438	0.6485	0.7921
Black	0.8495	0.4552	0.6538	0.8235	0.4228	0.6226	0.8030
Hispanic	0.8826	0.7126	0.7673	0.8726	0.4819	0.6273	0.7838
Controls:							
MSA FEs	Х	X	Х	X	Х	Х	Х
Demographics	Х	Х	Х	X	Х	Х	Х
Time * Region FEs	Х	X	X	X	Х	Х	Х
MSA-specific trends	Х	X	X	X	Х	Х	Х
Fully-interacted with race	Х	X	Х	X	Х	Х	Х
Sample:							
Full sample	Х	X	Х	X	Х	Х	Х

Table 7: Effects on employment for other groups

1 0		0	0
	White	Black	Hispanic
BTB – 0 to 1 year	-0.0079	-0.0265	-0.0161
	(0.0063)	(0.0167)	(0.0144)
BTB - 1 to 2 years	0.0006	-0.0514^{***}	-0.0301^{*}
	(0.0088)	(0.0182)	(0.0154)
BTB - 2 to 3 years	0.0089	-0.0406^{*}	-0.0257
	(0.0121)	(0.0216)	(0.0176)
BTB - 3 to 4 years	0.0083	-0.0839***	-0.0017
	(0.0150)	(0.0261)	(0.0315)
BTB - 4+ years	-0.0004	-0.0772^{**}	-0.0039
	(0.0157)	(0.0328)	(0.0352)
N	$373,\!237$	59,872	70,310
Pre-BTB baseline	0.8219	0.6770	0.7994
Controls:			
MSA FEs	Х	Х	Х
Demographics	Х	Х	Х
Time FEs	Х	Х	Х
MSA-specific trends	Х	Х	Х

Table 8: Effects on Employment for Men ages 25-34 with no college degree

* p < 0.10, ** p < $\overline{0.05}$, *** p < 0.01. Data source: CPS 2004-2014. Coefficients show the effect (in percentage points) of BTB on the probability of employment.

	White	Black	Hispanic
BTB	-0.0089	-0.0341^{**}	-0.0231*
	(0.0058)	(0.0154)	(0.0132)
BTB * private	0.0371^{***}	-0.0003	-0.0033
	(0.0135)	(0.0315)	(0.0204)
N	373,237	59,872	70,310
Pre-BTB baseline	0.8219	0.6770	0.7994
Controls:			
MSA FEs	Х	Х	Х
Demographics	Х	Х	Х
Time FEs	Х	Х	Х
MSA-specific trends	Х	Х	Х

Table 9: Effects on Employment for Men ages 25-34 with no college degree

* p < 0.10, ** p < 0.05, *** p < 0.01. Data source: CPS 2004-2014. Coefficients show the effect (in percentage points) of BTB on the probability of employment. BTB indicates any BTB law, while BTB * private indicates the local BTB law applies to at least some private firms.

A Appendix Figures and Tables

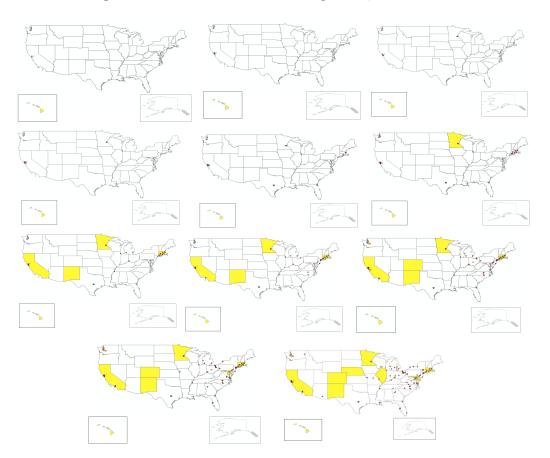


Figure A-1: Jurisdictions with BTB policies, 2004 to 2014

Maps are by year, beginning with 2004 in the top left corner, 2005 at the top center, 2006 at the top right, and continuing sequentially by row. Jurisdictions with BTB policies are represented by yellow shading (state-level policies), orange shading (county-level policies), and red dots (city-level policies.)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Percent Urban	0.0146^{***}						0.0062
	(0.0039)						(0.0067)
Percent Black		0.0146^{***}					0.0175^{**}
		(00053)					(0.0073)
Percent Hispanic			0.0083				0.0063
			(0.0075)				(0.0098)
Percent Poverty				-0.0116			-0.0296
				(0.0202)			(0.0301)
Percent Bachelor's Degree or More					0.0327^{**}		-0.0073
					(0.0133)		(0.0168)
Median FT Earnings (Male)						0.0001^{***}	0.0000
						(0.0000)	(0.0000)
N	51	51	51	51	51	51	51

Table A-1: Effect of state characteristics on BTB adoption

Notes: * p < 0.10, ** p < 0.05, *** p < 0.01. Outcome variable is whether any MSA in the state adopted BTB by December 2014. Dependent variables are measured at the state level in 2000.

Table A-2:	Effect of	pre-period	unemployment	on BTB	adoption

	BTB ever	BTB start date
2000 Unemployment	0.015	-1.061
	(0.016)	(1.309)
N	305	113
Sample:		
All MSAs	Х	
BTB-adopting MSAs		Х

Notes: * p < 0.10, ** p < 0.05, *** p < 0.01. Outcome variables are (1) whether the MSA adopted BTB by December 2014, and (2) conditional on ever adopting BTB, the month the policy was adopted. The coefficient implies the effect of the 2000 MSA-level unemployment rate on these outcomes.

	White	Black	Hispanic
BTB * Time	0.000	0.000	-0.001
	(0.001)	(0.003)	(0.002)
BTB	0.001	0.027	0.009
	(0.014)	(0.031)	(0.019)
Time	-0.000	-0.001	-0.000
	(0.001)	(0.002)	(0.002)
N	46,074	$7,\!436$	9,070

Table A-3: Test for differences in pre-period time trends

Notes: * p < 0.10, ** p < 0.05, *** p < 0.01. Outcome variable is the residual of our preferred specification, for men ages 25-34 who do not have a college degree. The samples match those in Figures 2–4. The coefficient of interest is *BTB* * *Time*, which reveals whether BTB-adopting and no-BTB MSAs have different pre-period trends in employment outcomes, conditional on the controls in our preferred specification.

$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	(5)	(9)	(1)	/~/
TB -0.0683*** -0.0559*** -0.0083 (0.0187) (0.0184) (0.0163) (0.0187) (0.0184) (0.0163) (0.0271) (0.0266) (0.0280) BTB -0.0946 *** -0.0873*** -0.0326 (0.0239) (0.0233) (0.0272) (0.0233) (0.0272) 0.0272] 0.0272) 0.0272]		$\left(\right)$	(\mathbf{y})	(8)
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$		0.0261	0.0244	0.0267
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	(0.0262)	(0.0273)	(0.0296)	(0.0274)
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	*** -0.1489***	-0.1346^{***}	-0.1366^{***}	-0.1392^{***}
BTB -0.0946^{***} -0.0873^{***} -0.0326 (0.0239) (0.0233) (0.0272) (0.0272) (0.0239) (0.0233) (0.0272) (0.0272) (0.0239) (0.0233) (0.0272) ((0.0377)	(0.0397)	(0.0402)	(0.0404)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	1	-0.1077^{***}	-0.0946^{***}	-0.1071^{***}
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	(0.0268)	(0.0302)	(0.0299)	(0.0305)
aseline 0.6844 0.6844 0.6844 0.4541 0.4541 0.4541 0.7287	6 $65,846$	43,075	28,595	43,075
$\begin{array}{cccccccccccccccccccccccccccccccccccc$				
0.4541 0.4541 0.4541 0.4541 0.7287 0.7287 0.7287 nics X X X X gion FEs X X X fic trends acted with race	4 0.6844	0.6879	0.6844	0.6879
0.7287 0.7287 0.7287 nics X X X gion FEs X X fic trends acted with race	1 0.4541	0.4504	0.4541	0.4504
nics X X X X X gion FEs X X X X X X X A A A A A A A A A A A A	7 0.7287	0.7219	0.7287	0.7219
X X X X X X X X X X X X X X X X X X X				
X X X X X X X A h race	Х	Х	Х	Х
X h race	Х	Х	Х	Х
h race	Х	Х	Х	Х
Fully-interacted with race	Х	Х	Х	Х
	Х	Х	Х	Х
MSA unemployment				Х
Sample:				
Full sample X X X X X	Х			
MSAs only		Х		Х
BTB-adopting only			Х	

probability of employment.

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	Drop AL	Drop AK	Drop AZ	Drop AR	Drop CA	Drop CO	Drop CT
White * BTB	-0.0025	-0.0026	-0.0028	-0.0025	-0.0016	-0.0014	-0.0030
	(0.0061)	(0.0061)	(0.0061)	(0.0061)	(0.0067)	(0.0064)	(0.0063)
Black * BTB	-0.0338**	-0.0333**	-0.0349^{**}	-0.0350**	-0.0306^{*}	-0.0323**	-0.0336**
	(0.0149)	(0.0148)	(0.0149)	(0.0149)	(0.0157)	(0.0151)	(0.0154)
Hispanic * BTB	-0.0234^{*}	-0.0233^{*}	-0.0239^{*}	-0.0235^{*}	-0.0238^{*}	-0.0344***	-0.0213
	(0.0130)	(0.0130)	(0.0134)	(0.0130)	(0.0122)	(0.0118)	(0.0139)
N	496,481	496,711	496,576	495,676	467,052	492,347	495,400
		D DC		D CA			БИ
	Drop DE	Drop DC	Drop FL	Drop GA	Drop HI	Drop ID	Drop IL
White * BTB	-0.0030	-0.0033	-0.0034	-0.0032	-0.0027	-0.0029	-0.0040
	(0.0063)	(0.0061)	(0.0062)	(0.0063)	(0.0061)	(0.0061)	(0.0063)
Black * BTB	-0.0366**	-0.0279**	-0.0386**	-0.0328**	-0.0343**	-0.0340**	-0.0325*
	(0.0151)	(0.0133)	(0.0145)	(0.0153)	(0.0149)	(0.0149)	(0.0169)
Hispanic * BTB	-0.0256^{*}	-0.0229*	-0.0230*	-0.0256*	-0.0252^{*}	-0.0233*	-0.0244*
	(0.0132)	(0.0131)	(0.0133)	(0.0132)	(0.0136)	(0.0132)	(0.0141)
Ν	495,456	499,741	485,197	492,170	501,213	496,261	488,433
	Drop IN	Drop IA	Drop KS	Drop KY	Drop LA	Drop ME	Drop MD
White * BTB	-0.0022	-0.0033	-0.0027	-0.0032	-0.0028	-0.0030	-0.0030
	(0.0061)	(0.0061)	(0.0062)	(0.0061)	(0.0061)	(0.0061)	(0.0063)
	(0.0001)		()			-0.0338**	
Black * BTB	-0.0330**	-0.0340**	-0.0357^{**}	-0.0337**	-0.0349**	-0.0558	-0.0383**
Black * BTB			-0.0357^{**} (0.0148)	-0.0337^{**} (0.0150)	(0.0349) (0.0153)	(0.0558)	(0.0383)
Black * BTB Hispanic * BTB	-0.0330**	-0.0340**					
	-0.0330^{**} (0.0175)	-0.0340^{**} (0.0149)	(0.0148)	(0.0150)	(0.0153)	(0.0148)	(0.0171)
	-0.0330** (0.0175) -0.0227*	-0.0340** (0.0149) -0.0238*	(0.0148) - 0.0220^*	(0.0150) - 0.0230^*	(0.0153) - 0.0224^*	(0.0148) - 0.0234^*	(0.0171) - 0.0242^*
Hispanic * BTB	-0.0330** (0.0175) -0.0227* (0.0129) 493,901	-0.0340** (0.0149) -0.0238* (0.0131) 493,365	$\begin{array}{c} (0.0148) \\ -0.0220^* \\ (0.0130) \\ \hline 495,607 \end{array}$	$\begin{array}{c} (0.0150) \\ -0.0230^* \\ (0.0130) \\ \hline 494,402 \end{array}$	(0.0153) -0.0224* (0.0129) 497,026	$\begin{array}{c} (0.0148) \\ -0.0234^* \\ (0.0130) \\ \hline 493,945 \end{array}$	$\begin{array}{c} (0.0171) \\ -0.0242^* \\ (0.0133) \\ \hline 494,161 \end{array}$
Hispanic * BTB	-0.0330** (0.0175) -0.0227* (0.0129) 493,901 Drop MA	-0.0340** (0.0149) -0.0238* (0.0131) 493,365 Drop MI	(0.0148) -0.0220* (0.0130) 495,607 Drop MN	(0.0150) -0.0230* (0.0130) 494,402 Drop MS	(0.0153) -0.0224* (0.0129) 497,026 Drop MO	(0.0148) -0.0234* (0.0130) 493,945 Drop MT	(0.0171) -0.0242* (0.0133) 494,161 Drop NE
Hispanic * BTB	-0.0330** (0.0175) -0.0227* (0.0129) 493,901 Drop MA -0.0020	-0.0340** (0.0149) -0.0238* (0.0131) 493,365 Drop MI -0.0051	(0.0148) -0.0220* (0.0130) 495,607 Drop MN -0.0049	(0.0150) -0.0230* (0.0130) 494,402 Drop MS -0.0036	(0.0153) -0.0224* (0.0129) 497,026 Drop MO -0.0026	(0.0148) -0.0234* (0.0130) 493,945 Drop MT -0.0030	(0.0171) -0.0242* (0.0133) 494,161 Drop NE -0.0033
Hispanic * BTB	-0.0330** (0.0175) -0.0227* (0.0129) 493,901 Drop MA -0.0020 (0.0062)	-0.0340** (0.0149) -0.0238* (0.0131) 493,365 Drop MI -0.0051 (0.0056)	(0.0148) -0.0220* (0.0130) 495,607 Drop MN -0.0049 (0.0060)	(0.0150) -0.0230* (0.0130) 494,402 Drop MS -0.0036 (0.0060)	(0.0153) -0.0224* (0.0129) 497,026 Drop MO -0.0026 (0.0062)	(0.0148) -0.0234* (0.0130) 493,945 Drop MT -0.0030 (0.0061)	(0.0171) -0.0242* (0.0133) 494,161 Drop NE -0.0033 (0.0063)
Hispanic * BTB	-0.0330** (0.0175) -0.0227* (0.0129) 493,901 Drop MA -0.0020 (0.0062) -0.0345**	-0.0340** (0.0149) -0.0238* (0.0131) 493,365 Drop MI -0.0051 (0.0056) -0.0323**	(0.0148) -0.0220* (0.0130) 495,607 Drop MN -0.0049 (0.0060) -0.0326**	(0.0150) -0.0230* (0.0130) 494,402 Drop MS -0.0036 (0.0060) -0.0326**	(0.0153) -0.0224* (0.0129) 497,026 Drop MO -0.0026 (0.0062) -0.0320**	(0.0148) -0.0234* (0.0130) 493,945 Drop MT -0.0030 (0.0061) -0.0338**	(0.0171) -0.0242* (0.0133) 494,161 Drop NE -0.0033 (0.0063) -0.0339**
Hispanic * BTB N White * BTB Black * BTB	-0.0330** (0.0175) -0.0227* (0.0129) 493,901 Drop MA -0.0020 (0.0062) -0.0345** (0.0150)	$\begin{array}{c} -0.0340^{**}\\ (0.0149)\\ -0.0238^{*}\\ (0.0131)\\ \hline 493,365\\ \hline \\ \hline \\ \hline \\ Drop MI\\ -0.0051\\ (0.0056)\\ -0.0323^{**}\\ (0.0156)\\ \end{array}$	$\begin{array}{c} (0.0148) \\ -0.0220^{*} \\ (0.0130) \\ \hline 495,607 \\ \hline \\ $	(0.0150) -0.0230* (0.0130) 494,402 Drop MS -0.0036 (0.0060) -0.0326** (0.0150)	(0.0153) -0.0224* (0.0129) 497,026 Drop MO -0.0026 (0.0062) -0.0320** (0.0148)	(0.0148) -0.0234* (0.0130) 493,945 Drop MT -0.0030 (0.0061) -0.0338** (0.0149)	$\begin{array}{c} (0.0171) \\ -0.0242^{*} \\ (0.0133) \\ \hline \\ 494,161 \\ \hline \\ \hline \\ \hline \\ \hline \\ 0.0033 \\ (0.0063) \\ -0.0339^{**} \\ (0.0148) \\ \end{array}$
Hispanic * BTB	-0.0330** (0.0175) -0.0227* (0.0129) 493,901 Drop MA -0.0020 (0.0062) -0.0345** (0.0150) -0.0238*	-0.0340** (0.0149) -0.0238* (0.0131) 493,365 Drop MI -0.0051 (0.0056) -0.0323** (0.0156) -0.0239*	(0.0148) -0.0220* (0.0130) 495,607 Drop MN -0.0049 (0.0060) -0.0326** (0.0155) -0.0228*	(0.0150) -0.0230* (0.0130) 494,402 Drop MS -0.0036 (0.0060) -0.0326** (0.0150) -0.0231*	(0.0153) -0.0224* (0.0129) 497,026 Drop MO -0.0026 (0.0062) -0.0320** (0.0148) -0.0232*	(0.0148) -0.0234* (0.0130) 493,945 Drop MT -0.0030 (0.0061) -0.0338** (0.0149) -0.0222*	(0.0171) -0.0242* (0.0133) 494,161 Drop NE -0.0033 (0.0063) -0.0339** (0.0148) -0.0228*
Hispanic * BTB N White * BTB Black * BTB	-0.0330** (0.0175) -0.0227* (0.0129) 493,901 Drop MA -0.0020 (0.0062) -0.0345** (0.0150)	$\begin{array}{c} -0.0340^{**}\\ (0.0149)\\ -0.0238^{*}\\ (0.0131)\\ \hline 493,365\\ \hline \\ \hline \\ \hline \\ Drop MI\\ -0.0051\\ (0.0056)\\ -0.0323^{**}\\ (0.0156)\\ \end{array}$	$\begin{array}{c} (0.0148) \\ -0.0220^{*} \\ (0.0130) \\ \hline 495,607 \\ \hline \\ $	(0.0150) -0.0230* (0.0130) 494,402 Drop MS -0.0036 (0.0060) -0.0326** (0.0150)	(0.0153) -0.0224* (0.0129) 497,026 Drop MO -0.0026 (0.0062) -0.0320** (0.0148)	(0.0148) -0.0234* (0.0130) 493,945 Drop MT -0.0030 (0.0061) -0.0338** (0.0149)	$\begin{array}{c} (0.0171) \\ -0.0242^{*} \\ (0.0133) \\ \hline \\ 494,161 \\ \hline \\ \hline \\ \hline \\ \hline \\ 0.0033 \\ (0.0063) \\ -0.0339^{**} \\ (0.0148) \\ \end{array}$

Table A-5: Effects on employment for men ages 25-34 with no college degree (Dropping AL-NE)

* p < 0.10, ** p < 0.05, *** p < 0.01. Data source: CPS 2004-2014. Coefficients show the effect (in percentage points) of BTB on the probability of employment.

	Drop NV	Drop NH	Drop NJ	Drop NM	Drop NY	Drop NC	Drop ND
White * BTB	-0.0028	-0.0041	0.0009	-0.0021	-0.0013	-0.0031	-0.0030
	(0.0061)	(0.0061)	(0.0059)	(0.0061)	(0.0062)	(0.0061)	(0.0062)
Black * BTB	-0.0335^{**}	-0.0336**	-0.0341^{**}	-0.0343**	-0.0350^{**}	-0.0346^{**}	-0.0341^{**}
	(0.0149)	(0.0149)	(0.0168)	(0.0149)	(0.0167)	(0.0154)	(0.0149)
Hispanic * BTB	-0.0225	-0.0243^{*}	-0.0339**	-0.0221^{*}	-0.0281^{*}	-0.0223^{*}	-0.0234^{*}
	(0.0140)	(0.0132)	(0.0165)	(0.0132)	(0.0152)	(0.0129)	(0.0131)
N	494,556	493,914	496,140	498,281	486,414	493,827	496,685
	Drop OH	Drop OK	Drop OR	Drop PA	Drop RI	Drop SC	Drop SD
White * BTB	-0.0024	-0.0029	-0.0009	-0.0007	-0.0031	-0.0033	-0.0028
TIMO DID	(0.0065)	(0.0061)	(0.0060)	(0.0061)	(0.0064)	(0.0061)	(0.0061)
Black * BTB	-0.0360**	-0.0341**	-0.0346**	-0.0324**	-0.0374**	-0.0290**	-0.0339**
	(0.0154)	(0.0148)	(0.0149)	(0.0154)	(0.0149)	(0.0138)	(0.0148)
Hispanic * BTB	-0.0212	-0.0234^*	-0.0245^{*}	-0.0283**	-0.0208	-0.0235^{*}	-0.0237^*
	(0.0129)	(0.0130)	(0.0132)	(0.0131)	(0.0128)	(0.0130)	(0.0130)
Ν	486,450	496,983	495,592	487,592	496,056	496,134	495,479
	Drop TN	Drop TX	Drop UT	Drop VT	Drop VA	Drop WA	Drop WV
		-	-	-	-	-0.0039	-0.0033
White * BTB	-0.0028	-0.0020	-0.0025	-0.0027	-0.0009	-0.0039	-0.0033
White * BTB							
	(0.0061)	(0.0061)	(0.0061)	(0.0062)	(0.0060)	(0.0062)	(0.0061)
White * BTB Black * BTB	(0.0061) - 0.0353^{**}	(0.0061) -0.0367**	(0.0061) - 0.0340^{**}	(0.0062) -0.0341**	(0.0060) - 0.0426^{***}	(0.0062) - 0.0350^{**}	(0.0061) - 0.0346^{**}
	(0.0061)	(0.0061)	(0.0061)	(0.0062)	(0.0060)	(0.0062)	(0.0061)
Black * BTB	(0.0061) - 0.0353^{**} (0.0151)	(0.0061) -0.0367** (0.0149)	(0.0061) - 0.0340^{**} (0.0149)	$\begin{array}{c} (0.0062) \\ -0.0341^{**} \\ (0.0149) \\ -0.0233^{*} \end{array}$	(0.0060) - 0.0426^{***} (0.0131)	(0.0062) - 0.0350^{**} (0.0149)	(0.0061) - 0.0346^{**} (0.0148) - 0.0234^{*}
Black * BTB	(0.0061) - 0.0353^{**} (0.0151) - 0.0233^{*}	$\begin{array}{c} (0.0061) \\ -0.0367^{**} \\ (0.0149) \\ -0.0215 \end{array}$	(0.0061) - 0.0340^{**} (0.0149) - 0.0228^{*}	(0.0062) -0.0341** (0.0149)	(0.0060) - 0.0426^{***} (0.0131) - 0.0221^{*}	(0.0062) - 0.0350^{**} (0.0149) - 0.0246^{*}	(0.0061) - 0.0346^{**} (0.0148)
Black * BTB Hispanic * BTB	(0.0061) -0.0353** (0.0151) -0.0233* (0.0130)	$\begin{array}{c} (0.0061) \\ -0.0367^{**} \\ (0.0149) \\ -0.0215 \\ (0.0130) \end{array}$	(0.0061) -0.0340** (0.0149) -0.0228* (0.0131)	$\begin{array}{c} (0.0062) \\ -0.0341^{**} \\ (0.0149) \\ -0.0233^{*} \\ (0.0131) \end{array}$	$\begin{array}{c} (0.0060) \\ -0.0426^{***} \\ (0.0131) \\ -0.0221^{*} \\ (0.0130) \end{array}$	(0.0062) - 0.0350^{**} (0.0149) - 0.0246^{*} (0.0135)	$\begin{array}{c} (0.0061) \\ -0.0346^{**} \\ (0.0148) \\ -0.0234^{*} \\ (0.0130) \end{array}$
Black * BTB Hispanic * BTB	$\begin{array}{c} (0.0061) \\ -0.0353^{**} \\ (0.0151) \\ -0.0233^{*} \\ (0.0130) \\ \hline 495,074 \end{array}$	$\begin{array}{c} (0.0061) \\ -0.0367^{**} \\ (0.0149) \\ -0.0215 \\ (0.0130) \\ \hline 473,775 \end{array}$	(0.0061) -0.0340** (0.0149) -0.0228* (0.0131)	$\begin{array}{c} (0.0062) \\ -0.0341^{**} \\ (0.0149) \\ -0.0233^{*} \\ (0.0131) \end{array}$	$\begin{array}{c} (0.0060) \\ -0.0426^{***} \\ (0.0131) \\ -0.0221^{*} \\ (0.0130) \end{array}$	(0.0062) - 0.0350^{**} (0.0149) - 0.0246^{*} (0.0135)	$\begin{array}{c} (0.0061) \\ -0.0346^{**} \\ (0.0148) \\ -0.0234^{*} \\ (0.0130) \end{array}$
Black * BTB Hispanic * BTB <u>N</u>	(0.0061) -0.0353** (0.0151) -0.0233* (0.0130) 495,074 Drop WI	(0.0061) -0.0367** (0.0149) -0.0215 (0.0130) 473,775 Drop WY	(0.0061) -0.0340** (0.0149) -0.0228* (0.0131)	$\begin{array}{c} (0.0062) \\ -0.0341^{**} \\ (0.0149) \\ -0.0233^{*} \\ (0.0131) \end{array}$	$\begin{array}{c} (0.0060) \\ -0.0426^{***} \\ (0.0131) \\ -0.0221^{*} \\ (0.0130) \end{array}$	(0.0062) - 0.0350^{**} (0.0149) - 0.0246^{*} (0.0135)	$\begin{array}{c} (0.0061) \\ -0.0346^{**} \\ (0.0148) \\ -0.0234^{*} \\ (0.0130) \end{array}$
Black * BTB Hispanic * BTB <u>N</u>	(0.0061) -0.0353** (0.0151) -0.0233* (0.0130) 495,074 Drop WI -0.0027	(0.0061) -0.0367** (0.0149) -0.0215 (0.0130) 473,775 Drop WY -0.0026	(0.0061) -0.0340** (0.0149) -0.0228* (0.0131)	$\begin{array}{c} (0.0062) \\ -0.0341^{**} \\ (0.0149) \\ -0.0233^{*} \\ (0.0131) \end{array}$	$\begin{array}{c} (0.0060) \\ -0.0426^{***} \\ (0.0131) \\ -0.0221^{*} \\ (0.0130) \end{array}$	(0.0062) - 0.0350^{**} (0.0149) - 0.0246^{*} (0.0135)	$\begin{array}{c} (0.0061) \\ -0.0346^{**} \\ (0.0148) \\ -0.0234^{*} \\ (0.0130) \end{array}$
Black * BTB Hispanic * BTB <u>N</u> White * BTB	$(0.0061) \\ -0.0353^{**} \\ (0.0151) \\ -0.0233^{*} \\ (0.0130) \\ 495,074 \\ \hline \\ Drop WI \\ -0.0027 \\ (0.0063) \\ \end{cases}$	(0.0061) -0.0367** (0.0149) -0.0215 (0.0130) 473,775 Drop WY -0.0026 (0.0062)	(0.0061) -0.0340** (0.0149) -0.0228* (0.0131)	$\begin{array}{c} (0.0062) \\ -0.0341^{**} \\ (0.0149) \\ -0.0233^{*} \\ (0.0131) \end{array}$	$\begin{array}{c} (0.0060) \\ -0.0426^{***} \\ (0.0131) \\ -0.0221^{*} \\ (0.0130) \end{array}$	(0.0062) - 0.0350^{**} (0.0149) - 0.0246^{*} (0.0135)	$\begin{array}{c} (0.0061) \\ -0.0346^{**} \\ (0.0148) \\ -0.0234^{*} \\ (0.0130) \end{array}$
Black * BTB Hispanic * BTB <u>N</u> White * BTB	(0.0061) -0.0353** (0.0151) -0.0233* (0.0130) 495,074 Drop WI -0.0027 (0.0063) -0.0356**	$\begin{array}{c} (0.0061) \\ -0.0367^{**} \\ (0.0149) \\ -0.0215 \\ (0.0130) \\ 473,775 \\ \hline \textbf{Drop WY} \\ -0.0026 \\ (0.0062) \\ -0.0345^{**} \end{array}$	(0.0061) -0.0340** (0.0149) -0.0228* (0.0131)	$\begin{array}{c} (0.0062) \\ -0.0341^{**} \\ (0.0149) \\ -0.0233^{*} \\ (0.0131) \end{array}$	$\begin{array}{c} (0.0060) \\ -0.0426^{***} \\ (0.0131) \\ -0.0221^{*} \\ (0.0130) \end{array}$	(0.0062) - 0.0350^{**} (0.0149) - 0.0246^{*} (0.0135)	$\begin{array}{c} (0.0061) \\ -0.0346^{**} \\ (0.0148) \\ -0.0234^{*} \\ (0.0130) \end{array}$
Black * BTB Hispanic * BTB N White * BTB Black * BTB	$\begin{array}{c} (0.0061)\\ -0.0353^{**}\\ (0.0151)\\ -0.0233^{*}\\ (0.0130)\\ \hline 495,074\\ \hline \textbf{Drop WI}\\ -0.0027\\ (0.0063)\\ -0.0356^{**}\\ (0.0150)\\ \end{array}$	$\begin{array}{c} (0.0061) \\ -0.0367^{**} \\ (0.0149) \\ -0.0215 \\ (0.0130) \\ \hline 473,775 \\ \hline \textbf{Drop WY} \\ -0.0026 \\ (0.0062) \\ -0.0345^{**} \\ (0.0149) \\ \end{array}$	(0.0061) -0.0340** (0.0149) -0.0228* (0.0131)	$\begin{array}{c} (0.0062) \\ -0.0341^{**} \\ (0.0149) \\ -0.0233^{*} \\ (0.0131) \end{array}$	$\begin{array}{c} (0.0060) \\ -0.0426^{***} \\ (0.0131) \\ -0.0221^{*} \\ (0.0130) \end{array}$	(0.0062) - 0.0350^{**} (0.0149) - 0.0246^{*} (0.0135)	$\begin{array}{c} (0.0061) \\ -0.0346^{**} \\ (0.0148) \\ -0.0234^{*} \\ (0.0130) \end{array}$

Table A-6: Effects on employment for men ages 25-34 with no college degree (Dropping NV-WY)

* p < 0.10, ** p < 0.05, *** p < 0.01. Data source: CPS 2004-2014. Coefficients show the effect (in percentage points) of BTB on the probability of employment.

	1 0	0	
	White	Black	Hispanic
BTB	-0.0012	-0.0168***	0.0069
	(0.0036)	(0.0047)	(0.0052)
N	373,237	59,872	70,310
Pre-BTB baseline	0.0581	0.0893	0.0618
Controls:			
MSA FEs	Х	Х	Х
Demographics	Х	Х	Х
Time FEs	Х	Х	Х
MSA-specific trends	s X	Х	Х

Table A-7: Effects on Public Sector Employment for Men ages 25-34 with no college degree

* p < 0.10, ** p < $\overline{0.05}$, *** p < 0.01. Data source: CPS 2004-2014. Coefficients show the effect (in percentage points) of BTB on the probability of employment.

Table A-8: Effect of BTB on the migration of men with no college degree

	Intra-County	Intra-State	Inter-State
Low-Skilled Men			
All Men	-0.0009	-0.0004	0.0009
	(0.0027)	(0.0011)	(0.0010)
Black Men	-0.0022	0.0004	-0.0028
	(0.0063)	(0.0037)	(0.0027)
Young Men	-0.0025	0.0007	0.0008
	(0.0055)	(0.0029)	(0.0028)
Young Black Men	-0.0281**	0.0034	-0.0072
	(0.0140)	(0.0073)	(0.0078)

Notes: * p < 0.10, ** p < 0.05, *** p < 0.01. Data source: March CPS Supplement 2004-2014. Each coefficients is the result of a separate regression, and shows the effect (in percentage points) of BTB on the probability that an individual moved within the previous year.