Hidden Costs of Ban the Box Laws: Unraveling the Effects on Drug-Related Deaths

Oleksandra Cheipesh *

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Abstract

Drawing on data from the National Vital Statistics System (NVSS), this study investigates the impact of Ban the Box (BTB) laws on drug-related mortality. Two years after adoption, BTB laws are associated with more than a 35 percent increase in drug-related mortality among Black and Hispanic men. The main mechanism driving this increase appears to be diminished labor opportunities. Consistent with the results of previous studies, I find evidence that BTB adoption reduces wages, the probability of employment, and the probability of full-time employment among Black and Hispanic men. This is the first study to provide evidence that BTB laws have negative spillover effects on drug-related fatalities.

Keywords: Ban the Box Laws, Drug-Related Mortality, Employment, Labor Market Outcomes

JEL codes: I12, J78, K31

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*Oleksandra Cheipesh: ocheipes@eco.uc3m.es, Universidad Carlos III de Madrid. I am grateful to Daniel I. Rees, Amanda Agan, Jan Stuhler, Francisca Antman, Warn N. Lekfuangfu, Yarine Fawaz, and participants of the UC3M Applied Reading Group for their comments and suggestions.

1 Introduction

Prescription drug monitoring programs (PDMPs) and Naloxone Access Laws (NALs) have been adopted by most states in an effort to tackle the ongoing opioid epidemic in the United States. There is some evidence that PDMPs and NALs are effective (Patrick et al., 2016; Rees et al., 2019), but there is less consensus regarding the social and economic determinants of illicit drug use. Based largely on descriptive evidence, Case and Deaton (2017) argue that poor labor market conditions have increased drug overdoses, suicides, and liver disease among White non-Hispanic men without a college degree. By contrast, Ruhm (2019) and Currie and Schwandt (2021) argue that economic conditions and labor market opportunities are, at best, only weakly predictive of the drug epidemic.

Leveraging the staggered adoption of Ban the Box (BTB) laws by 14 states during the period 2005-2020, this study provides new evidence on the causal relationship between labor market conditions and drug-related mortality. BTB laws delay criminal background checks until the later stages of the hiring process. Their proponents argue that BTB laws improve the employment prospects of individuals with prior convictions (hereafter, "ex-offenders"). However, there is an ongoing debate among scholars regarding the unintended consequences of BTB laws. Doleac and Hansen (2020) and Agan and Starr (2018) provide evidence that BTB laws encourage statistical discrimination and reduce job opportunities for racial and ethnic minorities without a college degree. Sabia et al. (2021) finds an increase in crime rates among Hispanic men when BTB laws are passed, suggesting that unintended consequences of BTB laws extend beyond the labor market.

In theory, the relationship between BTB laws and drug-related fatalities, at least in part, depends on the relationship between BTB laws and labor market outcomes. If BTB laws diminish employment opportunities for racial and ethnic minority groups, then their adoption could increase drug-related fatalities due to an increase in cumulative disadvantage, mental distress, and despair among these demographic groups (Case and Deaton, 2022). On the other hand, BTB laws could discourage the use of drugs and reduce drug-related fatalities among ex-offenders by improving their job prospects and increasing the opportunity cost of non-productive, often illicit, activities.

Using state-year level data from the National Vital Statistics System (NVSS) and employing an event study design, I find that one year after adoption, BTB laws are associated with a 22 to 27 percent increase in drug-related mortality among Black and Hispanic men (i.e., 2.7 to 4.5 deaths per 100,000 relative to the pre-treatment means). The association between BTB laws and drug-related mortality increases in magnitude during the first two years after BTB implementation but weakens in magnitude in subsequent years. A possible explanation for this pattern of results might be a change in the pool of individuals susceptible to the effects of BTB laws. In particular, the higher number of drug-related fatalities in the early stages of policy adoption might have contributed to a decrease in the number of individuals susceptible to the policy in subsequent years.

Interestingly, I find that BTB laws are positively associated with both opioid-related mortality and mortality from stimulants such as methamphetamine and cocaine. Similarly, the results show a positive relationship between BTB laws and drug-related mortality among both 16- through 34-year-old and 35- through 64-year-old Hispanic and Black men. These findings suggest that the impact of BTB laws is not limited to a specific age group or type of substance but affects a broad range of individuals within racial and ethnic minority groups.

To explore channels through which BTB laws may affect drug-related mortality, I utilize data from the American Community Survey (ACS) for the period 2005-2020. My results confirm those of previous studies, including Doleac and Hansen (2020) and Sabia et al. (2021). Specifically, I find that BTB decreases employment of Black men by 1.2 percentage points (1.45%) and Hispanic men by 0.73 percentage points (0.8%). Moreover, BTB laws are associated with reduced wages and a lower probability of full-time employment among Black and Hispanic men without a college degree. I also find evidence that BTB laws reduce the wages of White males without a college degree, but the estimated effects are smaller in magnitude and less precise.

Overall, the results suggest a negative association between BTB laws and job opportunities and a positive association between BTB laws and drug-related mortality for racial and ethnic minorities without a college degree. The findings of this study are broadly consistent with those documented by Pierce and Schott (2020), who exploit trade shocks to investigate the relationship between labor market outcomes and drug-related mortality during the period 1990-2013. Pierce and Schott (2020) provide evidence that exposure to a bill granting permanent normal trade relations to China is associated with a one-percentage-point increase in the unemployment rate and an increase in the death rate from drug overdoses of 2 to 3 deaths per 100,000. Their findings are of a smaller magnitude compared to the findings presented in this study, however, these disparities might be reconciled given that the drug epidemic after 2015 was characterized by the abuse of more lethal substances such as fentanyl.

The remainder of the paper is structured as follows. In Section 2, I provide background information on BTB laws and the relationship between labor market outcomes and drug use in the United States. I also discuss the reasons why BTB laws could affect drug use. In Section 3, I describe my data and empirical strategy. Baseline results and robustness checks are provided in Section 4. Section 5 concludes.

2 Background

2.1 Ban the Box Laws

Criminal background checks used to be a common practice during the hiring process in the United States. A 2012 survey conducted by the Society of Human Resource Management found that about 70 percent of employers were inquiring into applicants' conviction history (Sabia et al., 2021). Since a felony conviction reduces the probability of employment (Holzer et al., 2006; Holzer, 2009), opponents of criminal background checks argue that they are highly discriminatory against ex-offenders.

In 1998, Hawaii became the first state to adopt Ban the Box legislation, which delayed inquiring into applicants' conviction history until a conditional offer was made. This law applied to both the private and public sectors and remains one of the most influential Ban the Box practices in the United States. Following Hawaii's policy, by 2020, 36 states and over 150 localities had implemented similar laws in the public sector.[1] Additionally, laws in 37 localities also target government contractors, and fourteen states and 22 localities have extended Ban the Box policies to private-sector employment. Another key difference between these policies is the timing of when a criminal background check is permitted. This can vary, with some laws allowing for such checks after the initial job application is submitted, after an interview, or after a conditional job offer has been made.

The main part of the paper investigates the effect of BTB policies in states that have extended the law into the private sector without distinguishing between the timing of permitting criminal background checks. The focus on this type of law is driven by two factors. First, drug users are more likely to be risk-loving (Blondel et al., 2007), but individuals working in the public sector tend to be more risk-averse (Buurman et al., 2012). Second, even though workers are mobile and public sector BTB might affect employment in the private sector (Doleac and Hansen, 2020), according to the Bureau of Labor Statistics, only 15 percent of the workforce is employed in the public sector, resulting in a significantly lower share of affected individuals [2]. However, the results in the Appendix show that public sector BTB laws also lead to unintended consequences, although the estimated effects on both labor market outcomes and drug-related fatalities are smaller in absolute magnitude.

The effective dates of BTB laws' adoption in the private sector are presented in Table 1. The majority of states implemented BTB laws in the private sector after 2014, and both Republican-led and Democratic-led states have enacted these laws.

2.2 Previous Studies

This paper adds to two areas of research: the (un)intended consequences of Ban the Box policies and the effect of labor market outcomes on drug-related mortality. The effect of Ban the Box policies has been investigated on several outcomes including employment, composition of cities, and crime. By randomly assigning a felony con-

[1] In some cases, state laws apply to employment at the state, county, and city levels, while in other cases, they apply only to state employment.

[2] Considering that certain state laws do not extend to public employees in counties and cities, this percentage becomes even lower

Table 1. Effective Dates of Private Sector BTB

State	Jurisdiction	Effective Date
California	State	January 1, 2018
	Los Angeles	January 22, 2017
	San Francisco	August 13, 2014
Colorado	State	September 1, 2019
Connecticut	State	January 1, 2017
District of Columbia	DC	July 14, 2014
Illinois	State	January 1, 2015
	Chicago	January 1, 2015
Iowa	Waterloo	July 1, 2020
Hawai'i	State	July 15, 1998
Maryland	State	January 1, 2020
	Baltimore	August 13, 2014
	Montgomery County	January 1, 2015
	Prince George's County	January 20, 2015
Massachusetts	State	August 6, 2010
Minnesota	State	January 1, 2014
Missouri	Kansas City	June 9, 2018
	Columbia	December 1, 2014
New York	Buffalo	January 1, 2014
	New York City	October 27, 2015
	Rochester	November 18, 2014
	Suffolk County	August 25, 2020
	Westchester County	March 4, 2019
New Jersey	State	March 1, 2015
New Mexico	State	June 14, 2019
Oregon	State	January 1, 2016
	Portland	July 1, 2016
Pennsylvania	Philadelphia	July 12, 2011
Rhode Island	State	January 1, 2014
Texas	Austin	April 4, 2016
Vermont	State	July 1, 2017
Virginia	State	July 1, 2020
Washington	State	June 7, 2018
	Seattle	November 13, 2013
	Spokane	January 13, 2018

viction, Agan and Starr (2018) sent around 15,000 fictitious applications of otherwise identical Black and White men and women before and after BTB laws were in effect. They show that BTB policies widen an already existing call-back gap between White and Black applicants sixfold. Similarly, by utilizing geographic variation in BTB policies and data from the Current Population Survey, Doleac and Hansen (2020) find that the laws are associated with a decrease in the probability of employment for young Black and Hispanic men without a college degree. Negative employment effects are also found for ex-offenders (Jackson and Zhao, 2017b).

Contrary to these results, by utilizing the same identification strategy as Doleac and Hansen (2020) but extending the studied period to later years and distinguishing between various types of BTB laws, Kaestner and Wang (2023) finds no systematically statistically significant effects of BTB laws on employment of Black and Hispanic men. Moreover, Shoag and Veuger (2021) document that residents of neighborhoods with high crime rates experience an increase in employment following the adoption of the policy. The authors argue that this evidence suggests that the law is likely to benefit those with a prior conviction history. This result is also supported by Craigie (2020) who finds a positive relationship between public-sector BTB laws and employment opportunities of ex-offenders.

Several studies examine the effect of BTB laws on crime and recidivism. Jackson and Zhao (2017a) find a reduction in recidivism following the adoption of BTB laws, while Sherrard (2020) documents that the policy is associated with an increase in recidivism among Black men. Finally, Sabia et al. (2021) show that BTB laws are positively associated with criminal incidents involving Hispanic men without a college degree.

To the best of my knowledge, this paper is the first to study the effects of BTB laws on drug-related mortality. The main channel through which BTB laws may affect drug-related fatalities is a change in labor market opportunities after the adoption of BTB laws. There has been a long debate on the impact of employment opportunities on drug-related deaths. The earlier literature shows that recessions reduce liquor consumption, alcohol-involved driving, smoking, obesity, and mortality from all causes of fatalities but suicides (Ruhm, 1995; Ruhm, 2000; Ruhm, 2005). The author argues that a drop in income during economic downturns outweighs the psychological responses due to stress caused by recessions and results in decreased spending on alcohol and cigarettes. In another related paper, Ruhm (2019) studies the relationship between economic conditions and drug overdose deaths. Ruhm (2019) argues that even though mortality from drugs is positively associated with economic downturns, this relationship is rather spurious than causal.

However, there is a growing recent literature that documents a positive association between economic downturns and drug-related deaths. Case and Deaton (2017) suggest that the worsening of labor market conditions for White non-Hispanic men without college degrees attributed to an increase in deaths from suicide, alcohol-related, and drug-related causes. The authors hypothesize that this is due to a lack of jobs that provide prospects and a sense of belonging (Case and Deaton, 2022). These papers provide a valuable hypothesis on the death of despair which is evaluated by several quasi-experimental studies.

Carpenter et al. (2017) investigate the relationship between the state unemployment rate and the use of illicit drugs with the difference-in-difference strategy and data from the National Survey on Drug Use and Health (NSDUH). They find that the occurrence of substance use disorders related to marijuana, analgesics, hallucinogens, and alcohol is strongly affected by economic conditions with a tendency to increase during periods of economic downturns. Yet, their findings also suggest that the use of cocaine, crack, and LSD is highly pro-cyclical. Charles et al. (2019) document that a structural change in the manufacturing sector, that resulted in employment losses of less educated individuals, is associated with an increase in drug-related deaths, and the use of prescription opioids. Similar results are reported by Autor et al. (2019), Pierce and Schott (2020), and Adda and Fawaz (2020) who exploit trade shocks as a natural experiment to examine the effect of employment outcomes on substance abuse and mortality from drugs.

Exploiting the adoption of BTB laws in the private sector, this paper utilizes a novel natural experiment to provide evidence regarding the relationship between labor market outcomes and drug-related fatalities. A distinguishing aspect of this study is that BTB laws predominantly affect Black and Hispanic individuals in the labor market. This allows the study to provide evidence regarding the relationship between labor opportunities and drug-related mortality among racial and ethnic minority groups.

3 Data and Empirical Strategy

3.1 Data

In line with the previous studies, I focus on three racial groups: Black non-Hispanic, White non-Hispanic, and Hispanic. Mortality data come from the National Vital Statistics System multiple cause-of-death by bridged-race categories files during the period 2005-2020. The main results are presented for the total population by race to decrease zero values in the drug-related mortality rate. However, 4.3 shows the results by age group. Since Hawaii adopted BTB laws before the study period, it is excluded from the analysis in all regressions and specifications. As defined by the International Classification of Diseases, 10th Revision (ICD–10), the following codes were used to identify drug-related deaths: X40–X44 (unintentional), X60–X64 (suicide), X85 (homicide), and Y10–Y14 (undetermined). Among these deaths, the definition of opioid-related deaths is based on the multiple cause-of-death codes T40.0 (opium), T40.1 (heroin), T40.2 (other opioids), T40.3 (methadone), T40.4 (other synthetic narcotics), and T40.6 (other or unspecified narcotics) while T40.5 (cocaine) and T43.6 (psychostimulants with abuse potential) indicate deaths from stimulants such as cocaine and amphetamines.

Figure 1 shows the drug-related mortality rate per 100,000 men by race and origin from 2005 to 2020. Between 2005 and 2015 the biggest increase in drug-related mortality rate was among White men. However, since 2015, the drug-related mortality rate has increased by around 70 percent among White men, while it has more than tripled among Black men. The drug-related mortality rate among Hispanic men was the lowest over the whole period but during the last five years, the pace of increase has also been faster than for White men.

Compared to men, women had consistently lower drug-related death rates (Figure

2), but the pace of increase followed a similar pattern. Although the drug-related mortality rate among White women was higher than that among Hispanic and Black women over the observed period, the rise in the drug-related death rate between 2015 and 2020 was steeper among Black women.

To investigate the mechanisms through which BTB laws may affect the drug-related mortality rate, this study utilizes data from the American Community Survey during the period 2005-2020. The main analysis is drawn on the sample of individuals who are older than fifteen, do not attend school, and do not have a college degree.[3] The outcome variables are employment status, full-time employment, and the natural logarithm of wages. The employment variable takes a value of one if an individual is employed and zero otherwise. As the survey does not provide specific information on the reasons for being out of the labor force (i.e., retirement, disability, or other factors), the analysis focuses solely on individuals in the labor force. Full-time employment is a binary variable, taking a value of one if an individual's usual work hours per week are 35 or more. The analysis of full-time employment is restricted to individuals who are employed. To complement the analysis, the results from the Current Population Survey are shown in the Appendix.

3.2 Empirical Strategy

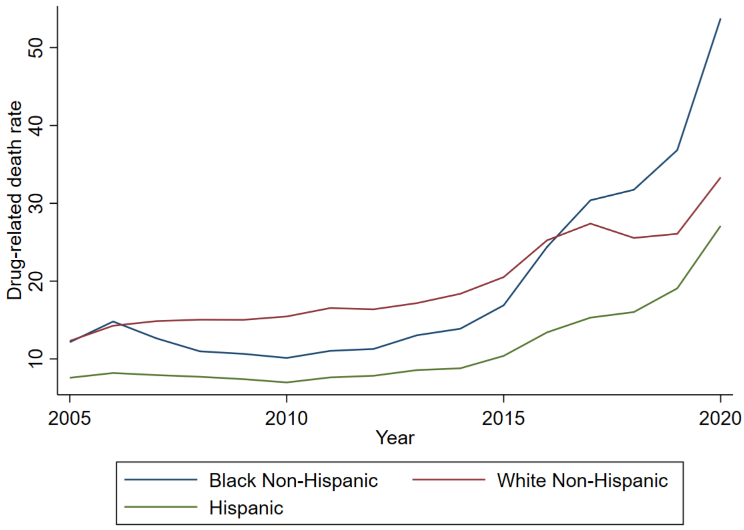
To estimate the short- and long-term effects of BTB laws on drug-related mortality I estimate the event study of the following form:

$$Y_{rgst} = \alpha + \sum_{j \neq -1} \pi_j D_s 1(t - BTB_s^* = j) + \gamma_s + \delta_t + \beta X_{rst} + \epsilon_{rst}$$

I utilize two estimation strategies: the Poisson model and the interaction-weighted estimator proposed by Sun and Abraham (2021). In the Poisson model, the dependent variable represents the number of drug-related deaths categorized by race (r) and

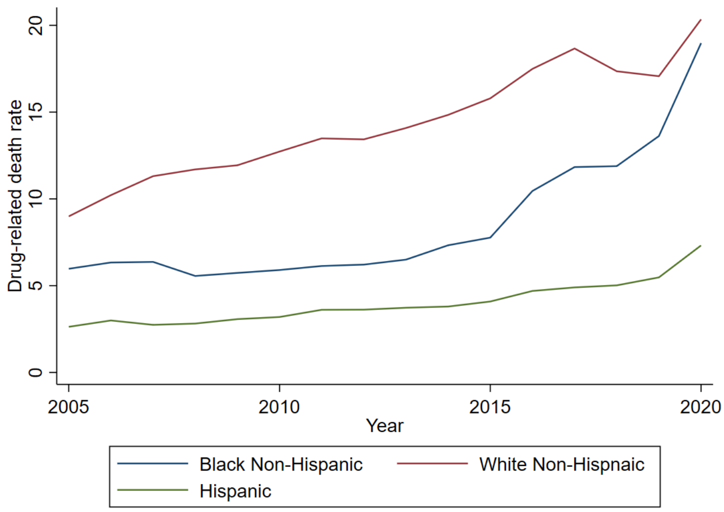
[3] Even though the National Vital Statistics System does not allow to explore the heterogeneity in drug-related mortality by educational level, it has been documented that individuals without college degrees experienced the biggest increase in drug-related mortality (Ho, 2017; Case and Deaton, 2017).

Figure 1. Drug-Related Mortality per 100,000 among Men



Note: The data come from the National Vital Statistic System. The number on the y-axis indicates the drug-related mortality per 100, 000 men

Figure 2. Drug-Related Mortality per 100,000 among Women



Note: The data come from the National Vital Statistic System. The number on the y-axis indicates the drug-related mortality per 100, 000 women gender (g) in state s and year t, with the population of the corresponding group serving as the exposure variable. The years before and after the adoption of BTB policies on a state level are denoted by $(t - BTB_s^* = j)$. γ_s is a set of state-fixed effects that account for state time-invariant characteristics and δ control for time-specific shocks. Finally, X_{st} include state-specific controls such as BTB laws that apply only to the public sector, medical and recreational marijuana laws, availability of the corresponding dispensaries, operational prescription drug monitoring program, Naloxone, and pill-mill laws, immigration policies such as e-verify mandates in public and private sectors, the natural logarithm of minimum wage, beer excise taxes, and income per capita in 2020 US dollars, the natural logarithm of police officers per 10,000 people and share of four age groups in the corresponding population (15-24, 25-34, 35-64 and over 64).[4]

The Poisson model is particularly suitable in this setting since unlike the log-linear model, it can handle zero values and accounts for the discrete nature of the data. Since the model indicates the exposure of each group, the coefficients can be interpreted as log points change in the number of deaths of a particular group over the corresponding population.

Since the recent literature has documented that difference-in-difference estimates might be biased if treatment effects are heterogeneous over time and groups, I also employ the interaction-weighted estimator proposed by Sun and Abraham (2021) to account for the potential problems with two-way fixed effects regressions (Goodman-Bacon, 2021; Sun and Abraham, 2021).[5] For this purpose, I estimate a log-linear model where the dependent variable is the natural logarithm of the drug-related death rate per 100,000. In this specification, I am weighting the regressions by the corresponding population.

[4]Intercensal estimates of population by race, Hispanic origin, sex, and age come from the Bureau Census. The income per capita data are from the Bureau of Economic Analysis, and the data on full-time equivalent police officers' employment are from the Census Bureau's Annual Survey of Public Employment

[5]The estimates from Poisson model in Section 4.1 suggest that the treatment effects are heterogeneous over time. Hence, the coefficients of lags and leads might be contaminated by effects from other periods (Sun and Abraham, 2021)

To investigate the effect of BTB laws on labor market outcomes, I estimate:

$$Y_{irgst} = \alpha_0 + \alpha_1 BTB_{st} + \alpha_2 X_{st} + \alpha_3 X_{irgst} + \gamma_s + \delta_t + \epsilon_{irgst},$$

where Y_{irgst} denotes labor market outcome of an individual i of race r and gender g in state s and year t. BTB_{st} is a binary variable if BTB law is adopted statewide in a given year; γ_s and δ_t denote state and time fixed effects; X_{st} are state-level controls such as BTB laws that apply only to the public sector, the natural logarithm of income per capita in \$2020, the minimum wage in 2020\$ and e-verify laws in private and public sectors; X_{irgst} include individual level control variables such as binary variables for marital status, parental status, high school completion, being in a certain age group (25-34, 35-64 and over 64), and citizenship status.[6]

4 Results

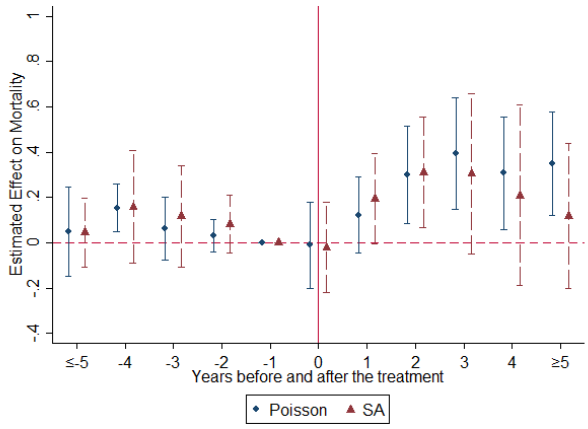
4.1 BTB Laws and Drug-Related Mortality

Figures 3 to 8 show the estimated effect of BTB laws on drug-related mortality obtained from a Poisson regression and the interaction-weighted estimator proposed by Sun and Abraham (2021). The standard errors in all the event studies are clustered at the state level.

Figure 3 illustrates the estimates for Black men. The coefficients from both the Poisson model and the interaction-weighted estimator provide limited evidence of a pre-trend but suggest a gradual increase in the drug-related death rate during the initial two years after policy adoption. After two years, BTB adoption is associated with a 37 percent increase ($e^{0.316} - 1$) in the drug-related mortality rate. Starting from the third year after the enactment of BTB laws, the association between BTB laws and the drug-related death rate weakens in both magnitude and precision. One possible explanation for this pattern of results might be a change in the susceptible population. The initial increase in drug-related fatalities during the early stages of

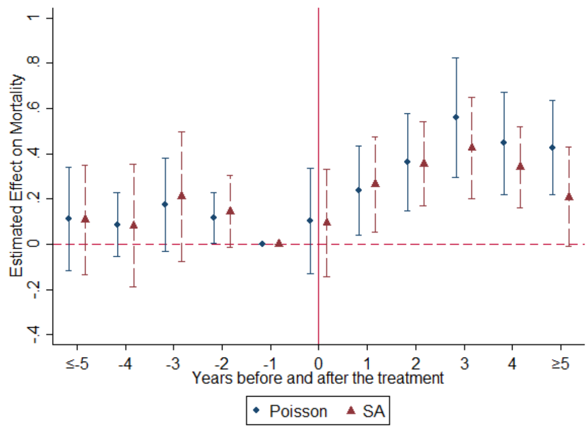
[6]Since the wages are reported for the previous year, the variable of interest and state-level controls are lagged when estimating the effect of BTB laws on the logarithm of wages

Figure 3. BTB and Drug-Related Mortality among Black Men: Poisson and SA Estimates



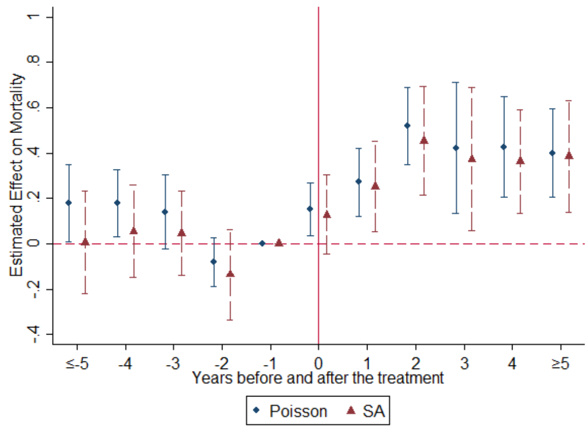
Notes: Based on the National Vital Statistics System data. The event-study estimates are obtained using a two-way fixed effects Poisson regression and the interaction-weighted estimator proposed by Sun and Abraham (SA). The dependent variable in the Poisson model is the number of drug-related deaths, with the corresponding population indicated as an exposure variable. The dependent variable in the SA model is the natural logarithm of drug-related death rate. The SA regression is weighted by the corresponding population. See Section 3.2 for a list of controls. The 95% confidence intervals are obtained with standard errors clustered at the state level.

Figure 4. BTB and Drug-Related Mortality among Black Women: Poisson and SA Estimates



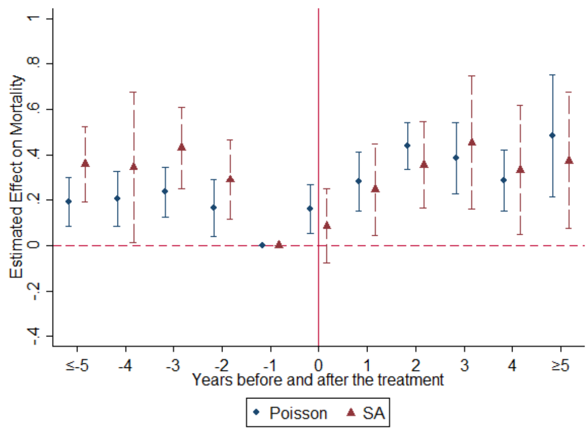
Notes: Based on the National Vital Statistics System data. The event-study estimates are obtained using a two-way fixed effects Poisson regression and the interaction-weighted estimator proposed by Sun and Abraham (SA). The dependent variable in the Poisson model is the number of drug-related deaths, with the corresponding population indicated as an exposure variable. The dependent variable in the SA model is the natural logarithm of drug-related death rate. The SA regression is weighted by the corresponding population. See Section 3.2 for a list of controls. The 95% confidence intervals are obtained with standard errors clustered at the state level.

Figure 5. BTB and Drug-Related Mortality among Hispanic Men: Poisson and SA Estimates



Based on the National Vital Statistics System data. The event-study estimates are obtained using a two-way fixed effects Poisson regression and the interaction-weighted estimator proposed by Sun and Abraham (SA). The dependent variable in the Poisson model is the number of drug-related deaths, with the corresponding population indicated as an exposure variable. The dependent variable in the SA model is the natural logarithm of drug-related death rate. The SA regression is weighted by the corresponding population. See Section 3.2 for a list of controls. The 95% confidence intervals are obtained with standard errors clustered at the state level.

Figure 6. BTB and Drug-Related Mortality among Hispanic Women: Poisson and SA Estimates



Based on the National Vital Statistics System data. The event-study estimates are obtained using a two-way fixed effects Poisson regression and the interaction-weighted estimator proposed by Sun and Abraham (SA). The dependent variable in the Poisson model is the number of drug-related deaths, with the corresponding population indicated as an exposure variable. The dependent variable in the SA model is the natural logarithm of drug-related death rate. The SA regression is weighted by the corresponding population. See Section 3.2 for a list of controls. The 95% confidence intervals are obtained with standard errors clustered at the state level.

policy adoption might have contributed to a reduction in the number of vulnerable individuals in subsequent years.

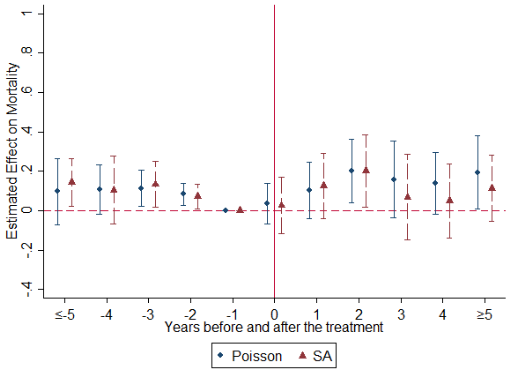
The results for Black women (Figure 4) show a similar pattern. The estimates of the lags indicate a slight downward trend in the drug-related mortality rate among Black women in treated states prior to the enactment of BTB laws. However, this trend might bias the results downward rather than upward. Following the enactment of BTB laws, the drug-related mortality rate among Black women begins to rise. Two years after policy adoption, BTB laws are associated with a 43 percent increase in the drug-related mortality rate. Four years after the policy adoption, the estimated effect of BTB laws on the drug-related mortality rate begins to weaken, which is similar to the pattern of results for Black men.

Figure 5 shows the estimates for Hispanic men. Similar to the pattern of findings for Black men and women, the estimates suggest a shift in the trend in the drug-related mortality rate among Hispanic men after the passage of BTB laws. The estimated effect of the policy on the drug-related mortality rate gradually increases during the first two years after policy adoption and remains constant in subsequent years. Poisson estimates for Hispanic women (Figure 6) also suggest a change in the trend in the drug-related mortality rate following the policy adoption. However, the estimates obtained with the interaction-weighted estimator provide no evidence of a change in the drug-related mortality rate following the adoption of BTB laws.

The coefficient plots for White men and women are presented in Figures 7 and 8. There is a slight increase in the drug-related death rate for White men following the adoption of BTB laws while the estimates for White women are small and not statistically significant at conventional levels. These findings are in line with previous studies by Doleac and Hansen (2020) and Sabia et al. (2021), as well as the results in Section 4.2, all of which suggest that White men and women appear to be the least affected by BTB laws.

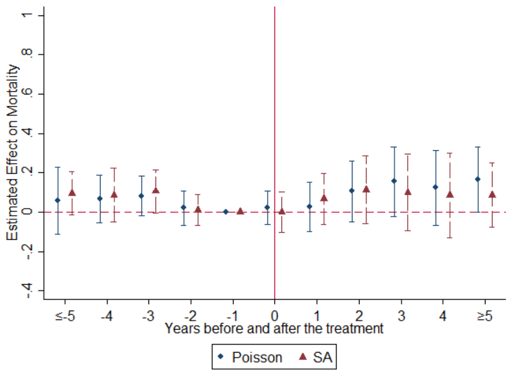
The estimates of the effects of public sector BTB laws on the drug-related mortality rate are shown in Figures A.1 to A.6. The findings suggest a modest increase in the drug-related mortality rate among Black men and women and Hispanic men after the passage of BTB laws. The magnitude of the increase is consistent with the

Figure 7. BTB and Drug-Related Mortality among White Men: Poisson and SA Estimates



Based on the National Vital Statistics System data. The event-study estimates are obtained using a two-way fixed effects Poisson regression and the interaction-weighted estimator proposed by Sun and Abraham (SA). The dependent variable in the Poisson model is the number of drug-related deaths, with the corresponding population indicated as an exposure variable. The dependent variable in the SA model is the natural logarithm of drug-related death rate. The SA regression is weighted by the corresponding population. See Section 3.2 for a list of controls. The 95% confidence intervals are obtained with standard errors clustered at the state level.

Figure 8. BTB and Drug-Related Mortality among White Women: Poisson and SA Estimates



Based on the National Vital Statistics System data. The event-study estimates are obtained using a two-way fixed effects Poisson regression and the interaction-weighted estimator proposed by Sun and Abraham (SA). The dependent variable in the Poisson model is the number of drug-related deaths, with the corresponding population indicated as an exposure variable. The dependent variable in the SA model is the natural logarithm of drug-related death rate. The SA regression is weighted by the corresponding population. See Section 3.2 for a list of controls. The 95% confidence intervals are obtained with standard errors clustered at the state level.

relationship between BTB laws and labor market outcomes presented in Section 4.2.

4.2 Mechanisms

Agan and Starr (2018) and Doleac and Hansen (2020) find that BTB laws increase statistical discrimination against racial and ethnic minorities without a college degree. Table 2 provides evidence confirming their results for the studied period and private sector BTB laws. The results suggest that the relationship between BTB laws and employment is stronger among Black and Hispanic individuals without a college degree than among their White counterparts. Following the policy adoption, the probabilities of employment and working full-time for Black men decrease by 1.2 percentage points (1.45%) and 1.7 percentage points (2%), respectively. For Hispanic men, BTB adoption is associated with a reduction in employment and full-time employment of 0.73 percentage points (0.8%) and 1.2 percentage points (1.3 %), respectively. The estimates for White men are smaller in absolute magnitude and less precise than for Black and Hispanic men. The results for women suggest the same pattern of results: the relationship between BTB laws and employment outcomes is larger in absolute magnitude among Black and Hispanic women.

The relationship between BTB laws and wages also appears to be the strongest among Black men. The estimates suggest that after the passage of BTB laws, wages of Black men declined by 5.5 percent $(1-e^{(-0.0567)})$. Similarly, after BTB, the wages of Black women declined more than the wages of their Hispanic and White counterparts.

Consistent with the studies by Doleac and Hansen (2020) and Sabia et al. (2021), the estimated employment effects are much less evident among individuals with a college degree. Table A.4 shows that only Hispanic men with a college degree experienced a reduction in the probability of full-time employment after the enactment of BTB laws. This estimated effect, however, is offset by White women with a college degree who experienced an increase in the probability of working full-time after BTB laws were passed. These findings suggest that BTB laws appear to disproportionately impact those who are already more susceptible to substance abuse, as the death of despair phenomenon is predominantly evident among individuals without a college

Table 2. BTB and Employment Outcomes among Individuals without a College Degree

	Men			Women		
	White	Black	Hispanic	White	Black	Hispanic
Employment	-0.0042	-0.0123**	-0.0073*	-0.0052*	-0.0089**	-0.0099**
	(0.0046)	(0.0047)	(0.0041)	(0.0031)	(0.0041)	(0.0046)
Pre-BTB Mean	0.929	0.847	0.921	0.936	0.870	0.898
N	4,573,531	633,740	1,228,691	3,551,655	654,261	852,815
Full-time Hours	-0.0046*	-0.0171***	-0.0116***	0.0014	-0.0135*	-0.0125**
	(0.0024)	(0.0039)	(0.0039)	(0.0040)	(0.0070)	(0.0056)
Pre-BTB Mean	0.873	0.834	0.882	0.703	0.759	0.727
N	4,252,550	537,406	1,133,514	3,325,614	569,482	768,335
Ln(Wage)	-0.0175*	-0.0567**	-0.0208	-0.0139	-0.0375***	-0.0079
	(0.0089)	(0.0274)	(0.0135)	(0.0087)	(0.0116)	(0.0129)
Pre-BTB Mean	49716.82	34549.81	35947.81	31561.15	28724.83	25879.47
N	4,019,617	587,891	1,101,690	3,246,548	591,797	766,667

Notes: Based on the American Community Survey data. The estimates are obtained with a two-way fixed effects OLS model. The dependent variables are binary variables for employment and full-time employment and the natural logarithm of wages. See Section 3.2 for a list of controls. The table reports the pre-BTB mean of wages instead of the logarithm of wages.
* statistically significant at the 10% level; ** at the 5% level, *** at the 1% level

degree (Case and Deaton, 2017).

Finally, Table A.2 shows the estimated effects of public sector BTB laws on the labor market outcomes of individuals without a college degree. Consistent with the earlier findings, the estimates suggest that the relationship between BTB laws and labor market outcomes is stronger among Black and Hispanic men and women compared to their White counterparts. However, the association between public sector BTB laws and labor outcomes is of a smaller absolute magnitude compared to the association between private sector BTB laws and labor market outcomes.

Overall, these findings provide compelling evidence that poor labor market outcomes among individuals without a college degree may have a detrimental impact on drug-related fatalities. Those who lack higher education already face a higher risk of substance abuse. Therefore, laws that diminish their labor market opportunities appear to further exacerbate this problem.

Considering that the current drug epidemic is driven by more lethal substances such as fentanyl, the estimates of the effects of BTB laws on drug-related mortality are consistent with previous studies that examined the relationship between labor market conditions and drug-related mortality. The findings of this study suggest that the employment of Black and Hispanic men decreased by approximately one percentage point after the passage of BTB laws. The drug-related mortality rate of this demographic group increased by approximately 25 percent in the first year after the passage of BTB laws and by approximately 40 percent in the second year after the passage of BTB laws (i.e., 2.5 to 4 deaths per 100,000 and 5.5 to 6 deaths per 100,000 relative to the pre-treatment means shown in Table A.1). Pierce and Schott (2020) documents that exposure to a bill granting permanent normal trade relations to China is associated with a one-percentage-point increase in the unemployment rate and an increase in the death rate from drug overdoses of 2 to 3 deaths per 100,000.

4.3 Heterogeneity and Robustness Checks

Figure A.7 presents heterogeneity by two age groups: 15-34 and 35-64. The estimates for Black individuals and Hispanic men suggest that both age groups experienced an increase in the drug-related mortality rate after BTB laws were enacted. Whereas, consistent with the main results, Sun and Abraham (2021) estimates do not provide evidence of a change in drug-related mortality trends for Hispanic women and White individuals of any age group following the implementation of BTB laws. The estimates in Table A.3 indicate that estimated effects of BTB laws on labor market outcomes are also evident among both 16- through 34-year-old and 35- through 64-year-old Hispanic and Black men. After the passage of BTB laws, the younger age group experienced a higher incidence of job losses, while the older age group had a lower probability of working full-time.[7]

Figure A.8 shows the results by type of drugs: opioids vs stimulants. BTB laws

[7] The estimated effects of BTB laws on employment for the older age group differ from those reported by Doleac and Hansen (2020) and Sabia et al. (2021). The main reason for this difference is that this study focuses on private-sector BTB laws and covers the period up to 2020.

are positively associated with both opioid-related mortality and mortality from stimulants. This pattern of results suggests that the effect of BTB laws is not limited to a specific type of substance, but affects a wide range of individuals within racial and ethnic minority groups.

Table A.5 in the Appendix shows the employment effects examined with the data from the Current Population Survey. The outcomes related to employment and full-time hours are from the CPS monthly survey, while wage data is obtained from the CPS annual supplement. The estimates indicate a decrease in the probability of being employed among Black men and a reduction in the probability of working full-time among Hispanic men following the adoption of BTB laws. Furthermore, based on the CPS data, the estimated effect of BTB laws on wages is the largest in absolute magnitude for Hispanic men. The estimates for Black women do not reach statistical significance at conventional levels. However, their magnitude is comparable to the estimates obtained with the ACS data. The estimated effects for Hispanic women are inconclusive since the estimated effect on employment is positive but the estimated effects on full-time-employment and wages are negative. Moreover, none of the estimates for Hispanic women is statistically significant.

Figures A.9 to A.14 in the Appendix show the event studies with a different set of controls. First, I only include the most common controls in the literature which are factors that have been shown to directly affect drug-related deaths and the share of age groups.[8] Second, I enrich the main model with a control variable which denotes a share of the state affected by BTB laws if the treatment took place on the county or city level. The share is constructed as the population of a city or county in 2003 divided by the state population in 2003. I chose this year because the first public BTB law after Hawaii was adopted in 2005.[9] The estimates with an alternative set of controls are comparable to those from the main specification.

Next, I check if Sun and Abraham (2021) estimates are robust to estimating

[8]These factors include BTB in the public sector, PDMP, "pill mill" regulations, Naloxone provision, medical and recreational marijuana laws, as well as the availability of corresponding dispensaries

[9]I do not control for the share of the state affected by public sector BTB because city/county public employment is small and not proportional to the population in a given jurisdiction.

a log-linear model without missing values. To address the issue with missing values resulting from taking the logarithm of zero, I add a constant to the dependent variable. This constant is set to half of the minimum positive value of the drug-related death rate within the corresponding group. By doing so, I ensure that all observations have non-zero values, enabling the logarithmic transformation without missing data. Figures A.15 to A.20 in the Appendix do not provide any evidence that estimates are of different magnitude and statistical significance.

One threat to identification might arise from time-varying unobservable factors that may affect Black and Hispanic individuals. For instance, the prices of drugs may decrease over time in certain states, or there might be an increase in the supply of more lethal substances such as fentanyl. To address these potential issues, I incorporate state-specific trends into the model. The estimates obtained from the regressions that account for state-specific trends are depicted in Figures A.21 to A.26 in the Appendix. The coefficients suggest similar findings, indicating no specific pre-trends, but an increase in drug-related mortality among Black individuals and Hispanic men following the adoption of BTB laws.

5 Conclusion

Ban the Box laws are gaining popularity across the United States. By 2020, 37 states had adopted some form of the BTB policy with the goal of improving employment opportunities among ex-offenders. However, several studies have highlighted that BTB laws might lead to statistical discrimination against ethnic and racial minority groups, diminishing employment opportunities for Hispanic and Black individuals (Doleac and Hansen, 2020; Agan and Starr, 2018).

Using data from the National Vital Statistics System, this study investigates the impact of BTB laws on drug-related mortality. The event-study estimates suggest that the adoption of BTB laws in the private sector is associated with an increase in drug-related fatalities among Black individuals and Hispanic men. One year after the adoption of BTB laws, the drug-related mortality rate among Black and Hispanic men increased by 22 to 27 percent; two years after the adoption of BTB laws, the drug-related mortality rate among Black and Hispanic men increased by more than 35 percent.

The main mechanisms driving this relationship appear to be diminished labor opportunities resulting from statistical discrimination against Black and Hispanic individuals without a college degree. The estimated effects of BTB laws on employment and wages drawing on data from the ACS and CPS are consistent with the results suggested by Doleac and Hansen (2017) and Sabia et al. (2021). The findings indicate that BTB laws are associated with a reduction in wages, the probability of employment, and the probability of full-time employment among racial and ethnic minority groups without a college degree.

These results suggest a negative relationship between labor opportunities and drug-related mortality, corroborating the discussions put forth by Case and Deaton (2017) and the findings of Autor et al. (2019); Pierce and Schott (2020) and Charles et al. (2019). Consequently, addressing demand factors in substance abuse might be crucial to effectively combat the drug epidemic.

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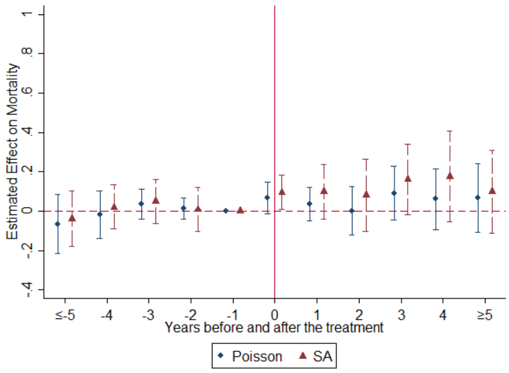
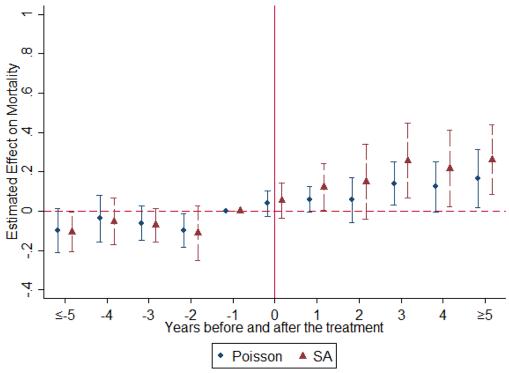
A Appendix

Figure A.1. Public Sector BTB and Drug-Related Mortality among Black Men: Poisson and SA Estimates



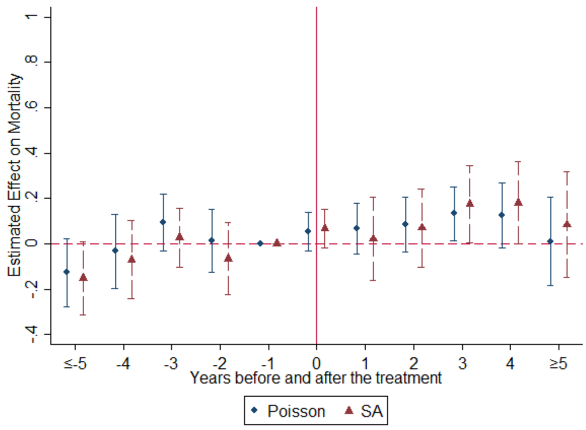
Notes: Based on the National Vital Statistics System data. The event-study estimates are obtained using a two-way fixed effects Poisson regression and the interaction-weighted estimator proposed by Sun and Abraham (SA). The dependent variable in the Poisson model is the number of drug-related deaths, with the corresponding population indicated as an exposure variable. The dependent variable in the SA model is the natural logarithm of drug-related death rate. The SA regression is weighted by the corresponding population. See Section 3.2 for a list of controls. The 95% confidence intervals are obtained with standard errors clustered at the state level.

Figure A.2. Public Sector BTB and Drug-Related Mortality among Black Women: Poisson and SA Estimates



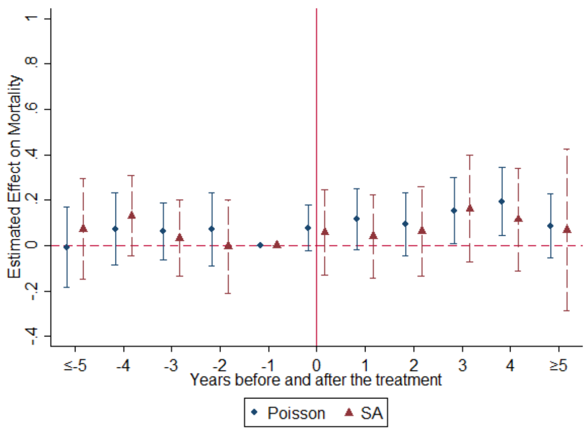
Notes: Based on the National Vital Statistics System data. The event-study estimates are obtained using a two-way fixed effects Poisson regression and the interaction-weighted estimator proposed by Sun and Abraham (SA). The dependent variable in the Poisson model is the number of drug-related deaths, with the corresponding population indicated as an exposure variable. The dependent variable in the SA model is the natural logarithm of drug-related death rate. The SA regression is weighted by the corresponding population. See Section 3.2 for a list of controls. The 95% confidence intervals are obtained with standard errors clustered at the state level.

Figure A.3. Public Sector BTB and Drug-Related Mortality among Hispanic Men: Poisson and SA Estimates



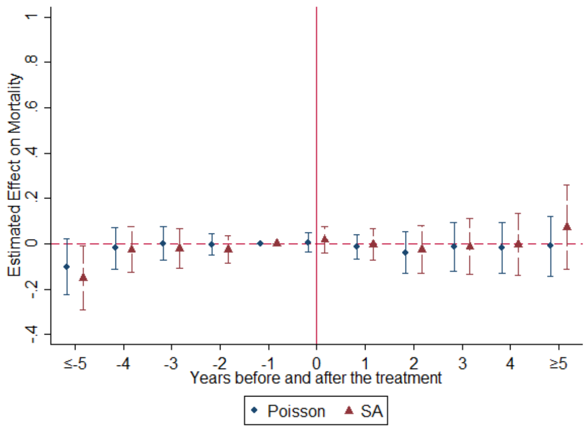
Based on the National Vital Statistics System data. The event-study estimates are obtained using a two-way fixed effects Poisson regression and the interaction-weighted estimator proposed by Sun and Abraham (SA). The dependent variable in the Poisson model is the number of drug-related deaths, with the corresponding population indicated as an exposure variable. The dependent variable in the SA model is the natural logarithm of drug-related death rate. The SA regression is weighted by the corresponding population. See Section 3.2 for a list of controls. The 95% confidence intervals are obtained with standard errors clustered at the state level.

Figure A.4. Public Sector BTB and Drug-Related Mortality among Hispanic Women: Poisson and SA Estimates



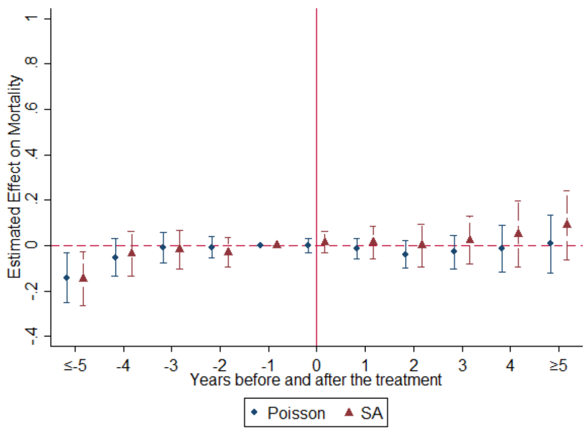
Based on the National Vital Statistics System data. The event-study estimates are obtained using a two-way fixed effects Poisson regression and the interaction-weighted estimator proposed by Sun and Abraham (SA). The dependent variable in the Poisson model is the number of drug-related deaths, with the corresponding population indicated as an exposure variable. The dependent variable in the SA model is the natural logarithm of drug-related death rate. The SA regression is weighted by the corresponding population. See Section 3.2 for a list of controls. The 95% confidence intervals are obtained with standard errors clustered at the state level.

Figure A.5. Public Sector BTB and Drug-Related Mortality among White Men: Poisson and SA Estimates



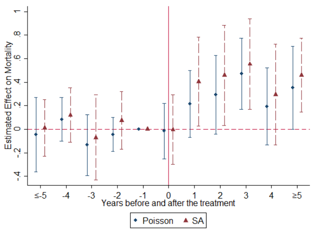
Based on the National Vital Statistics System data. The event-study estimates are obtained using a two-way fixed effects Poisson regression and the interaction-weighted estimator proposed by Sun and Abraham (SA). The dependent variable in the Poisson model is the number of drug-related deaths, with the corresponding population indicated as an exposure variable. The dependent variable in the SA model is the natural logarithm of drug-related death rate. The SA regression is weighted by the corresponding population. See Section 3.2 for a list of controls. The 95% confidence intervals are obtained with standard errors clustered at the state level.

Figure A.6. Public Sector BTB and Drug-Related Mortality among White Women: Poisson and SA Estimates

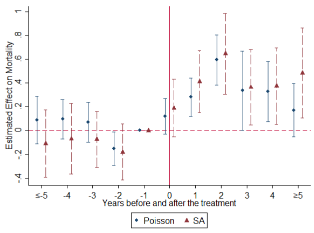


Based on the National Vital Statistics System data. The event-study estimates are obtained using a two-way fixed effects Poisson regression and the interaction-weighted estimator proposed by Sun and Abraham (SA). The dependent variable in the Poisson model is the number of drug-related deaths, with the corresponding population indicated as an exposure variable. The dependent variable in the SA model is the natural logarithm of drug-related death rate. The SA regression is weighted by the corresponding population. See Section 3.2 for a list of controls. The 95% confidence intervals are obtained with standard errors clustered at the state level.

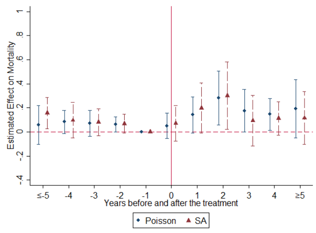
Figure A.7. BTB and Drug-Related Mortality: Heterogeneity By Age



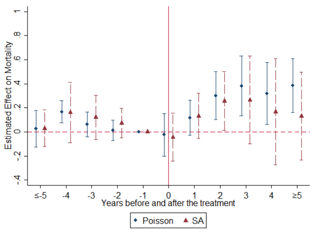
(a) BM 15-34



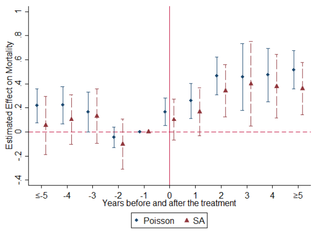
(b) HM 15-34



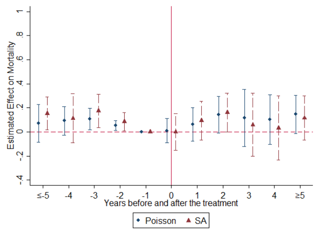
(c) WM 15-34



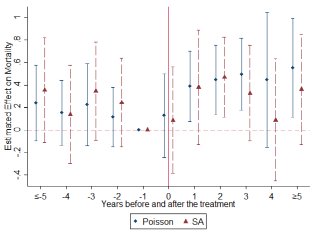
(d) BM 35-64



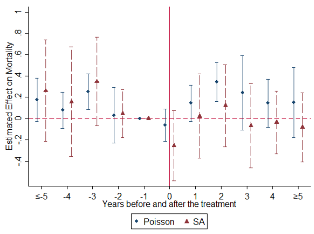
(e) HM 35-64



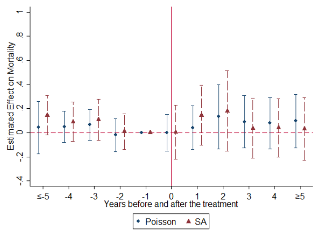
(f) WM 35-64



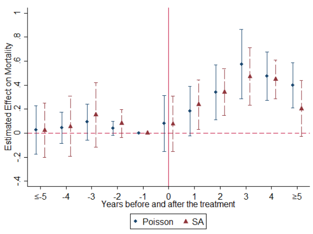
(g) BF 15-34



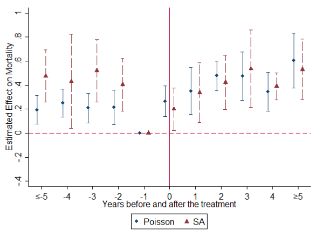
(h) HF 15-34



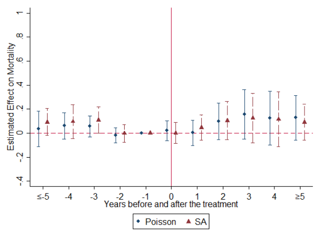
(i) WF 15-34



(j) BF 35-64



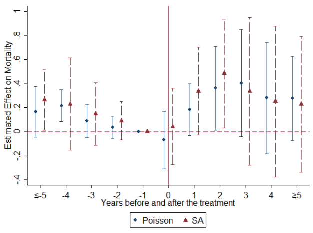
(k) HF 35-64



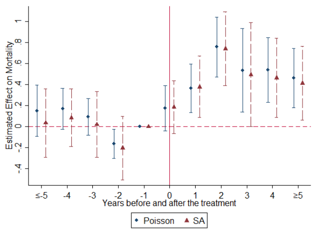
(l) WF 35-64

Notes: Based on the National Vital Statistics System data. The following event studies present heterogeneity by two age groups: 15-34, and 35-64 among Black men (BM), Hispanic men (HM), White men (WM), Black women (BW), Hispanic Women (HW), and White Women (WM). The estimates are obtained using a two-way fixed effects Poisson regression and the interaction-weighted estimator proposed by Sun and Abraham (SA). The dependent variable in the Poisson model is the number of drug-related deaths, with the corresponding population indicated as an exposure variable. The dependent variable in the SA model is the natural logarithm of the drug-related death rate. SA regressions are weighted by the corresponding population. See Section 3.2 for a list of controls. The 95% confidence intervals are obtained with standard errors clustered at the state level.

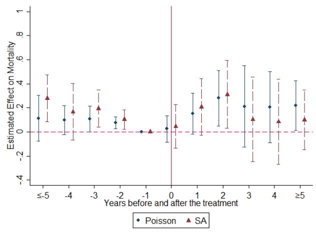
Figure A.8. BTB and Drug-Related Mortality: Heterogeneity By Drug Type



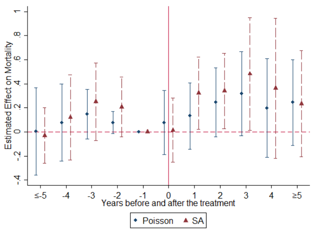
(a) BM Opioids



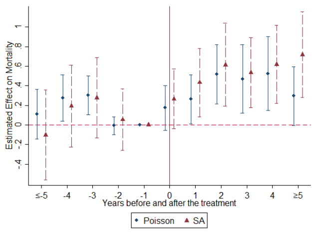
(b) HM Opioids



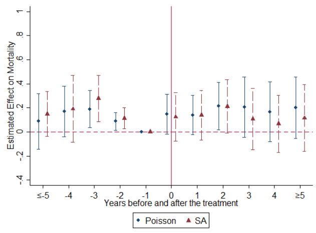
(c) WM Opioids



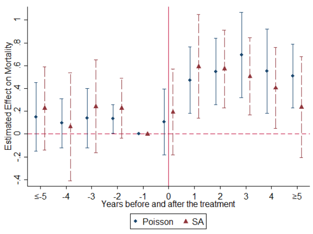
(d) BM Stimulants



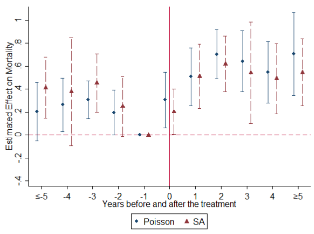
(e) HM Stimulants



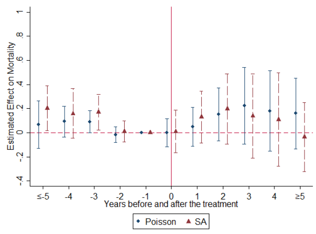
(f) WM Stimulants



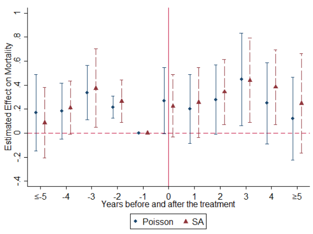
(g) BF Opioids



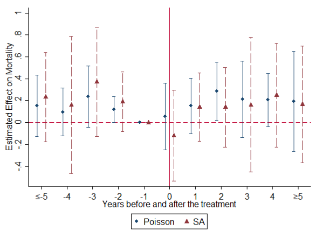
(h) HF Opioids



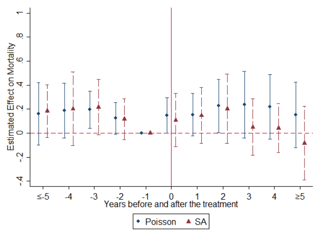
(i) WF Opioids



(j) BF Stimulants



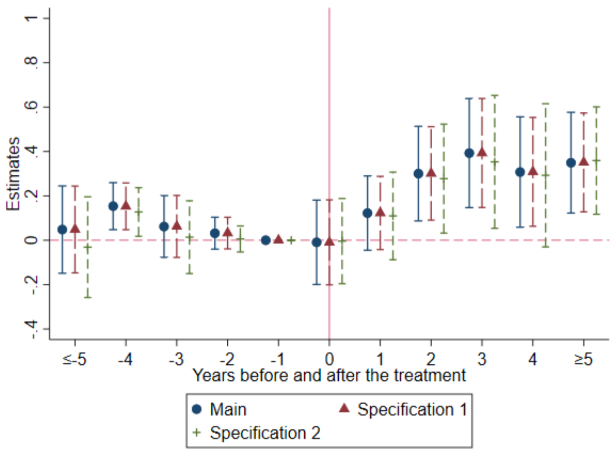
(k) HF Stimulants



(l) WF Stimulants

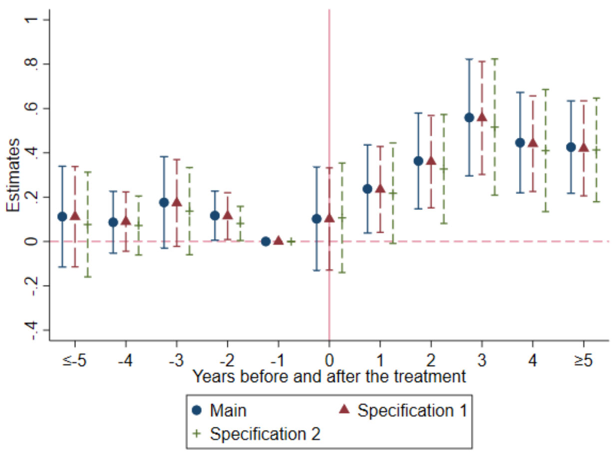
Notes: Based on the National Vital Statistics System data. The following event studies present heterogeneity by drug type (opioids vs. stimulants) among Black men (BM), Hispanic men (HM), White men (WM), Black women (BW), Hispanic Women (HW), and White Women (WM). The estimates are obtained using a two-way fixed effects Poisson regression and the interaction-weighted estimator proposed by Sun and Abraham (SA). The dependent variable in the Poisson model is the number of drug-related deaths, with the corresponding population indicated as an exposure variable. The dependent variable in the SA model is the natural logarithm of the drug-related death rate. SA regressions are weighted by the corresponding population. See Section 3.2 for a list of controls. The 95% confidence intervals are obtained with standard errors clustered at the state level.

Figure A.9. BTB and Drug-Related Mortality among Black Men: Sensitivity Check



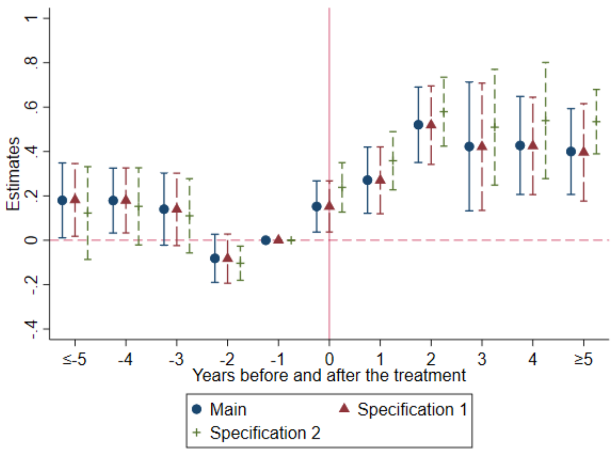
Notes: Based on the National Vital Statistics System data. The event-study estimates are obtained using a two-way fixed effects Poisson regression. The dependent variable is the number of drug-related deaths, with the corresponding population indicated as an exposure variable. The main specification includes the full set of controls, specification two includes a reduced set of controls, and specification three adds share treated to the main specification. The 95% confidence intervals are obtained with standard errors clustered at the state level.

Figure A.10. BTB and Drug-Related Mortality among Black Women: Sensitivity Check



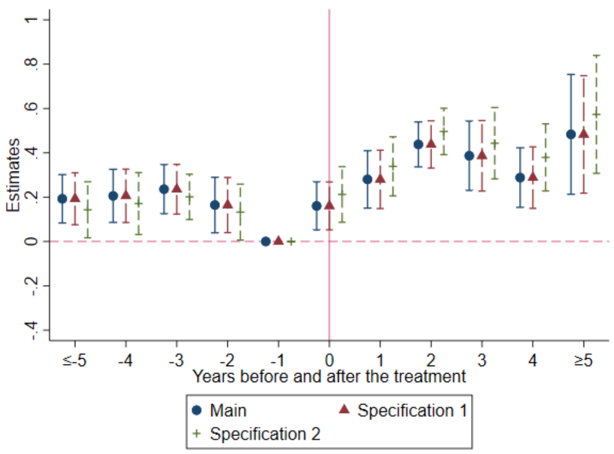
Notes: Based on the National Vital Statistics System data. The event-study estimates are obtained using a two-way fixed effects Poisson regression. The dependent variable is the number of drug-related deaths, with the corresponding population indicated as an exposure variable. The main specification includes the full set of controls, specification two includes a reduced set of controls, and specification three adds share treated to the main specification. The 95% confidence intervals are obtained with standard errors clustered at the state level.

Figure A.11. BTB and Drug-Related Mortality among Hispanic Men: Sensitivity Check



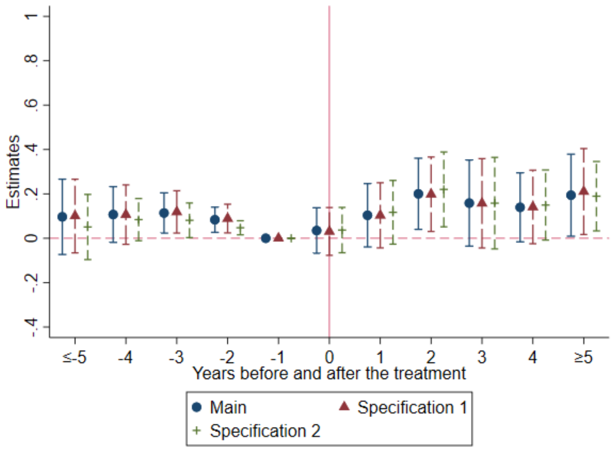
Notes: Based on the National Vital Statistics System data. The event-study estimates are obtained using a two-way fixed effects Poisson regression. The dependent variable is the number of drug-related deaths, with the corresponding population indicated as an exposure variable. The main specification includes the full set of controls, specification two includes a reduced set of controls, and specification three adds share treated to the main specification. The 95% confidence intervals are obtained with standard errors clustered at the state level.

Figure A.12. BTB and Drug-Related Mortality among Hispanic Women: Sensitivity Check



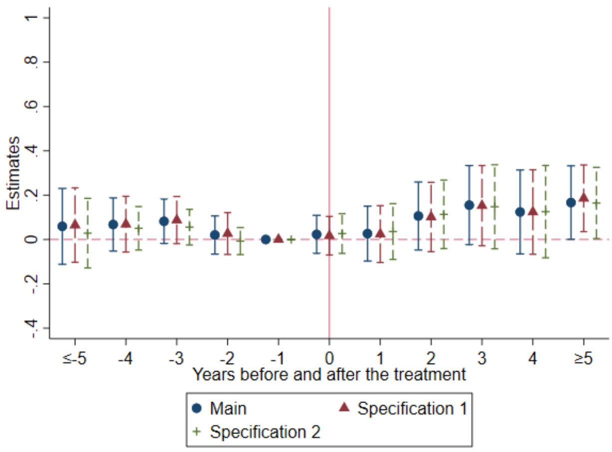
Notes: Based on the National Vital Statistics System data. The event-study estimates are obtained using a two-way fixed effects Poisson regression. The dependent variable is the number of drug-related deaths, with the corresponding population indicated as an exposure variable. The main specification includes the full set of controls, specification two includes a reduced set of controls, and specification three adds share treated to the main specification. The 95% confidence intervals are obtained with standard errors clustered at the state level.

Figure A.13. BTB and Drug-Related Mortality among White Men: Sensitivity Check



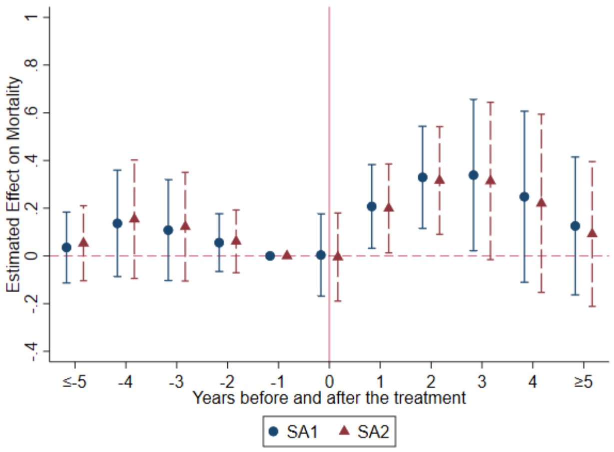
Notes: Based on the National Vital Statistics System data. The event-study estimates are obtained using a two-way fixed effects Poisson regression. The dependent variable is the number of drug-related deaths, with the corresponding population indicated as an exposure variable. The main specification includes the full set of controls, specification two includes a reduced set of controls, and specification three adds share treated to the main specification. The 95% confidence intervals are obtained with standard errors clustered at the state level.

Figure A.14. BTB and Drug-Related Mortality among White Women: Sensitivity Check



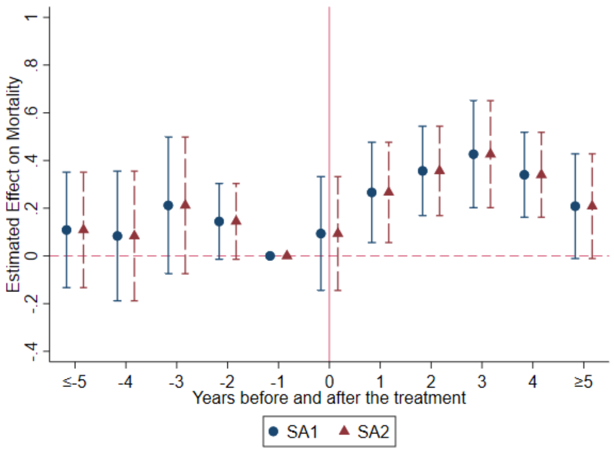
Notes: Based on the National Vital Statistics System data. The event-study estimates are obtained using a two-way fixed effects Poisson regression. The dependent variable is the number of drug-related deaths, with the corresponding population indicated as an exposure variable. The main specification includes the full set of controls, specification two includes a reduced set of controls, and specification three adds share treated to the main specification. The 95% confidence intervals are obtained with standard errors clustered at the state level.

Figure A.15. BTB and Drug-Related Mortality: SA Estimates for Black Men



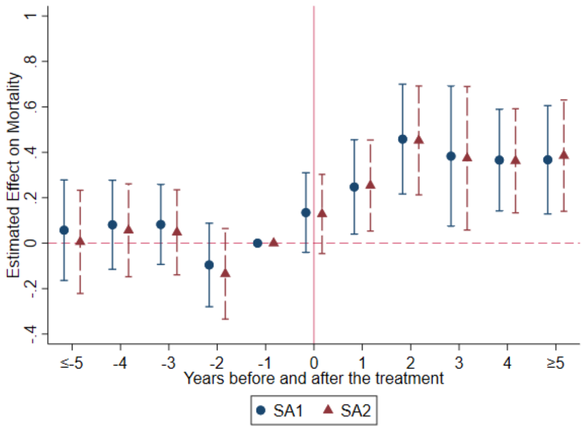
Notes: Based on the National Vital Statistics System data. The estimates are obtained with the interaction-weighted estimator proposed by Sun and Abraham (SA). The dependent variable in the SA1 specification is the natural logarithm of the drug-related death rate per 100, 000; the SA2 specification's dependent variable is the natural logarithm of the drug-related death rate per 100,000 with an added constant. Both specifications include the full set of control variables and are weighted by the corresponding population. The 95% confidence intervals are obtained with standard errors clustered at the state level.

Figure A.16. BTB and Drug-Related Mortality: SA Estimates for Black Women



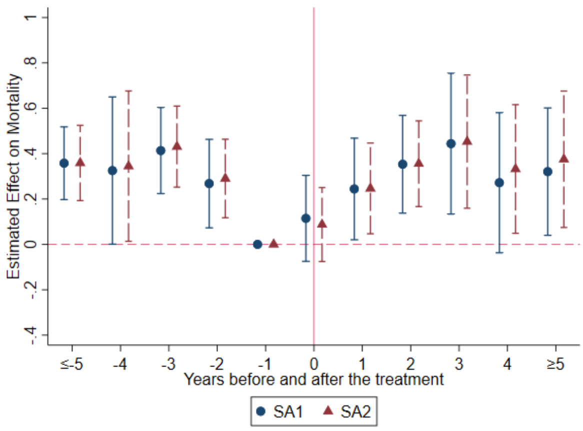
Notes: Based on the National Vital Statistics System data. The estimates are obtainted with the interaction-weighted estimator proposed by Sun and Abraham (SA). The dependent variable in the SA1 specification is the natural logarithm of the drug-related death rate per 100, 000; the SA2 specification's dependent variable is the natural logarithm of the drug-related death rate per 100,000 with an added constant. Both specifications include the full set of control variables and are weighted by the corresponding population. The 95% confidence intervals are obtained with standard errors clustered at the state level.

Figure A.17. BTB and Drug-Related Mortality: SA Estimates for Hispanic Men



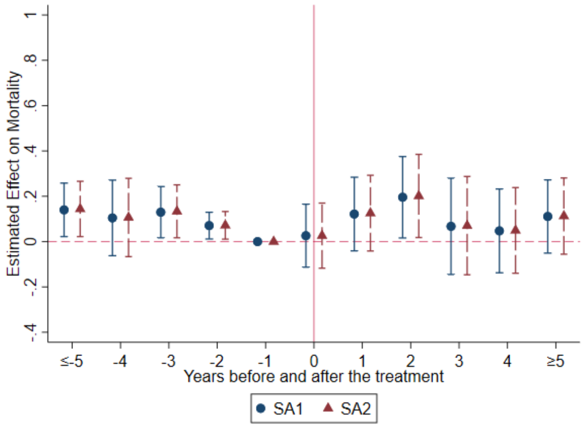
Notes: Based on the National Vital Statistics System data. The estimates are obtainted with the interaction-weighted estimator proposed by Sun and Abraham (SA). The dependent variable in the SA1 specification is the natural logarithm of the drug-related death rate per 100, 000; the SA2 specification's dependent variable is the natural logarithm of the drug-related death rate per 100,000 with an added constant. Both specifications include the full set of control variables and are weighted by the corresponding population. The 95% confidence intervals are obtained with standard errors clustered at the state level.

Figure A.18. BTB and Drug-Related Mortality: SA Estimates for Hispanic Women



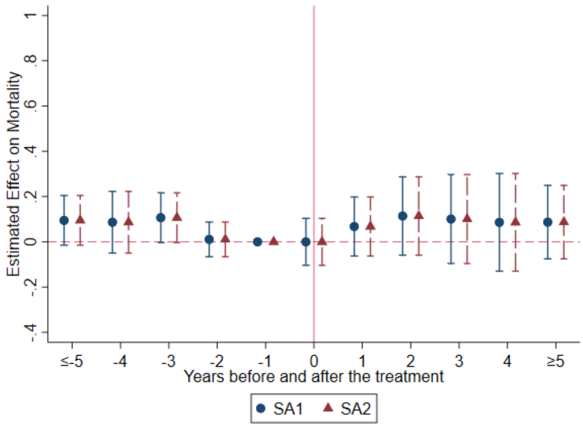
Notes: Based on the National Vital Statistics System data. The estimates are obtainted with the interaction-weighted estimator proposed by Sun and Abraham (SA). The dependent variable in the SA1 specification is the natural logarithm of the drug-related death rate per 100, 000; the SA2 specification's dependent variable is the natural logarithm of the drug-related death rate per 100,000 with an added constant. Both specifications include the full set of control variables and are weighted by the corresponding population. The 95% confidence intervals are obtained with standard errors clustered at the state level.

Figure A.19. BTB and Drug-Related Mortality: SA Estimates for White Men



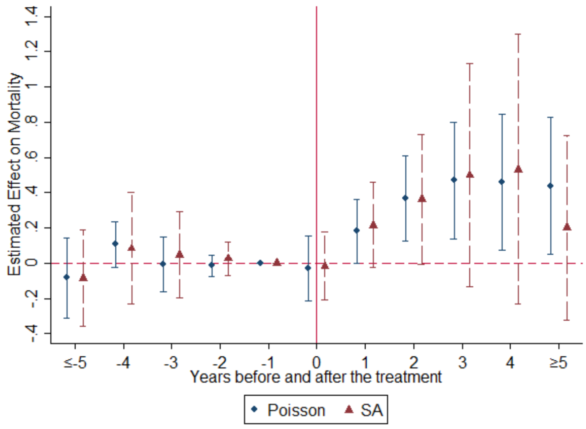
Notes: Based on the National Vital Statistics System data. The estimates are obtainted with the interaction-weighted estimator proposed by Sun and Abraham (SA). The dependent variable in the SA1 specification is the natural logarithm of the drug-related death rate per 100, 000; the SA2 specification's dependent variable is the natural logarithm of the drug-related death rate per 100,000 with an added constant. Both specifications include the full set of control variables and are weighted by the corresponding population. The 95% confidence intervals are obtained with standard errors clustered at the state level.

Figure A.20. BTB and Drug-Related Mortality: SA Estimates for White Women



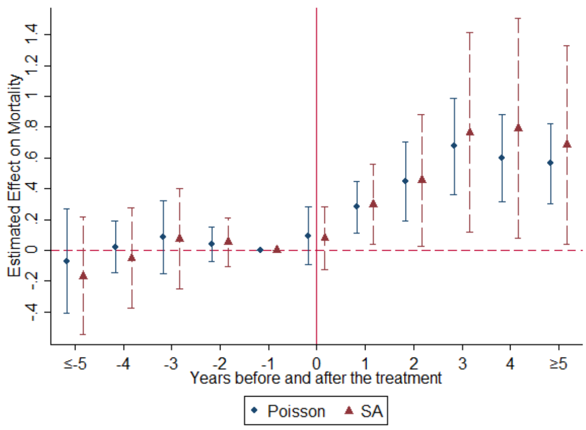
Notes: Based on the National Vital Statistics System data. The estimates are obtainted with the interaction-weighted estimator proposed by Sun and Abraham (SA). The dependent variable in the SA1 specification is the natural logarithm of the drug-related death rate per 100, 000; the SA2 specification's dependent variable is the natural logarithm of the drug-related death rate per 100,000 with an added constant. Both specifications include the full set of control variables and are weighted by the corresponding population. The 95% confidence intervals are obtained with standard errors clustered at the state level.

Figure A.21. BTB and Drug-Related Mortality among Black Men with State-Specific Trends



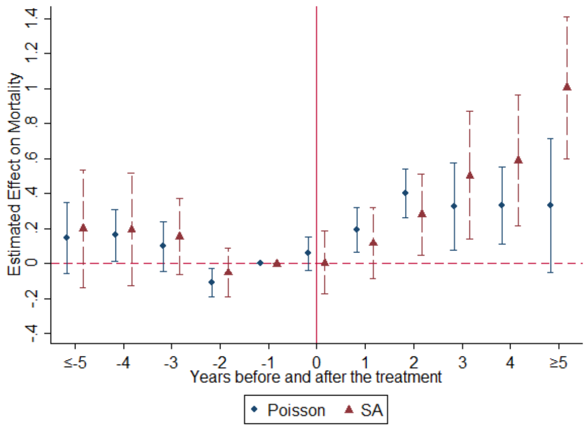
Notes: Based on the National Vital Statistics System data. The event-study estimates are obtained using a two-way fixed effects Poisson regression and the interaction-weighted estimator proposed by Sun and Abraham (SA). The dependent variable in the Poisson model is the number of drug-related deaths, with the corresponding population indicated as an exposure variable. The dependent variable in the SA model is the natural logarithm of the drug-related death rate. SA regressions are weighted by the corresponding population. See Section 3.2 for a list of controls. The 95% confidence intervals are obtained with standard errors clustered at the state level.

Figure A.22. BTB and Drug-Related Mortality among Black Women with State-Specific Trends



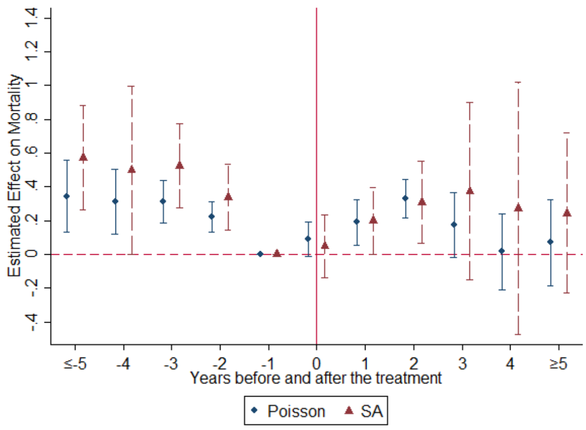
Notes: Based on the National Vital Statistics System data. The event-study estimates are obtained using a two-way fixed effects Poisson regression and the interaction-weighted estimator proposed by Sun and Abraham (SA). The dependent variable in the Poisson model is the number of drug-related deaths, with the corresponding population indicated as an exposure variable. The dependent variable in the SA model is the natural logarithm of the drug-related death rate. SA regressions are weighted by the corresponding population. See Section 3.2 for a list of controls. The 95% confidence intervals are obtained with standard errors clustered at the state level.

Figure A.23. BTB and Drug-Related Mortality among Hispanic Men with State-Specific Trends



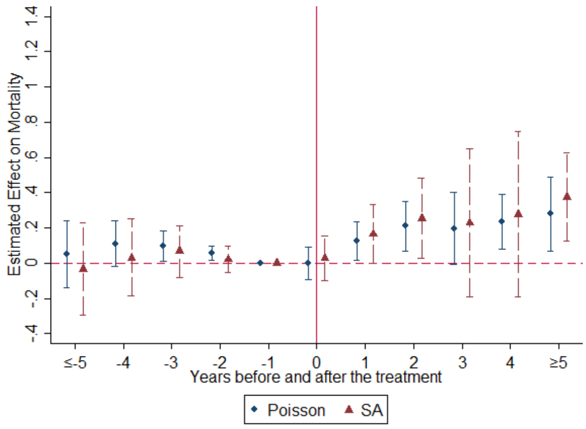
Notes: Based on the National Vital Statistics System data. The event-study estimates are obtained using a two-way fixed effects Poisson regression and the interaction-weighted estimator proposed by Sun and Abraham (SA). The dependent variable in the Poisson model is the number of drug-related deaths, with the corresponding population indicated as an exposure variable. The dependent variable in the SA model is the natural logarithm of the drug-related death rate. SA regressions are weighted by the corresponding population. See Section 3.2 for a list of controls. The 95% confidence intervals are obtained with standard errors clustered at the state level.

Figure A.24. BTB and Drug-Related Mortality among Hispanic Women with State-Specific Trends



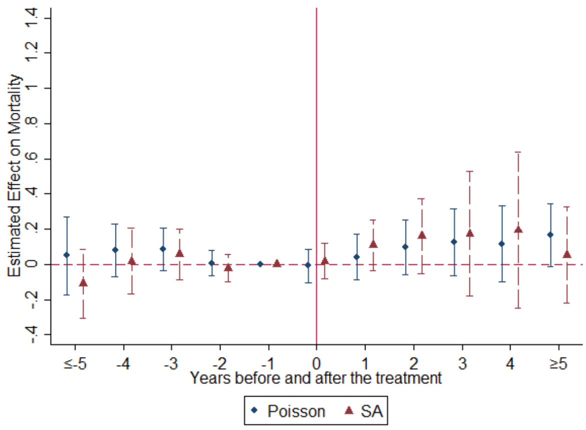
Notes: Based on the National Vital Statistics System data. The event-study estimates are obtained using a two-way fixed effects Poisson regression and the interaction-weighted estimator proposed by Sun and Abraham (SA). The dependent variable in the Poisson model is the number of drug-related deaths, with the corresponding population indicated as an exposure variable. The dependent variable in the SA model is the natural logarithm of the drug-related death rate. SA regressions are weighted by the corresponding population. See Section 3.2 for a list of controls. The 95% confidence intervals are obtained with standard errors clustered at the state level.

Figure A.25. BTB and Drug-Related Mortality among White Men with State-Specific Trends



Notes: Based on the National Vital Statistics System data. The event-study estimates are obtained using a two-way fixed effects Poisson regression and the interaction-weighted estimator proposed by Sun and Abraham (SA). The dependent variable in the Poisson model is the number of drug-related deaths, with the corresponding population indicated as an exposure variable. The dependent variable in the SA model is the natural logarithm of the drug-related death rate. SA regressions are weighted by the corresponding population. See Section 3.2 for a list of controls. The 95% confidence intervals are obtained with standard errors clustered at the state level.

Figure A.26. BTB and Drug-Related Mortality among White Women with State-Specific Trends



Notes: Based on the National Vital Statistics System data. The event-study estimates are obtained using a two-way fixed effects Poisson regression and the interaction-weighted estimator proposed by Sun and Abraham (SA). The dependent variable in the Poisson model is the number of drug-related deaths, with the corresponding population indicated as an exposure variable. The dependent variable in the SA model is the natural logarithm of the drug-related death rate. SA regressions are weighted by the corresponding population. See Section 3.2 for a list of controls. The 95% confidence intervals are obtained with standard errors clustered at the state level.

Table A.1. Pre-Treatment Summary Statistics Of Drug-Related Mortality Rate by Race and Gender

	Men			Women		
	White	Black	Hispanic	White	Black	Hispanic
Mean	22.76	20.49	10.20	14.26	10.26	4.17
St. Dev.	12.60	19.24	9.80	6.40	9.97	4.57
Min	1.71	0	0	0	0	0
Max	106.28	174.82	61.84	92.54	45.73	43.24

Notes: The data come from the National Vital Statistic System. Drug-related mortality rate is per 100, 000 of the corresponding population

Table A.2. Public Sector BTB and Employment Outcomes among Individuals without a College Degree

	Men			Women		
	White	Black	Hispanic	White	Black	Hispanic
Employment	-0.0023	-0.0086***	-0.0052**	-0.0032	-0.0085***	-0.0086***
	(0.0029)	(0.0030)	(0.0024)	(0.0023)	(0.0024)	(0.0030)
Pre-BTB Mean	0.927	0.841	0.923	0.933	0.865	0.900
N	4,573,531	633,740	1,228,691	3,551,655	654,261	852,815
Full-time Hours	-0.0029**	-0.0074***	-0.0105***	0.0015	-0.0058	-0.0073
	(0.0014)	(0.0021)	(0.0031)	(0.0020)	(0.0036)	(0.0045)
Pre-BTB Mean	0.877	0.837	0.891	0.706	0.763	0.738
N	4,252,550	537,406	1,133,514	3,325,614	569,482	768,335
Ln(Wage)	0.0031	-0.0046	-0.0057	-0.0043	-0.0128	-0.0144*
	(0.0050)	(0.0105)	(0.0092)	(0.0040)	(0.0094)	(0.0079)
Pre-BTB Mean	49382.6	33984.4	35681.47	31123.84	27986.22	25410.84
N	4,019,617	587,891	1,101,690	3,246,548	591,797	766,667

Notes: Based on the American Community Survey data. The estimates are obtained with a two-way fixed effects OLS model. The dependent variables are binary variables for employment and full-time employment and the natural logarithm of wages. See Section 3.2 for a list of controls. The table reports the pre-BTB mean of wages instead of the logarithm of wages.

* statistically significant at the 10% level; ** at the 5% level, *** at the 1% level

Table A.3. BTB and Employment Outcomes among Individuals without a College Degree: Heterogeneity by Age

	Men			Women		
	White	Black	Hispanic	White	Black	Hispanic
Aged 16-34						
Employment	-0.0037	-0.0141*	-0.0089**	-0.0065	-0.0107	-0.0202***
	(0.0060)	(0.0073)	(0.0040)	(0.0043)	(0.0070)	(0.0059)
Pre-BTB Mean	0.893	0.769	0.900	0.889	0.790	0.865
N	1,207,736	207,756	496,578	772,587	196,728	306,249
Full-time Hours	-0.0089	-0.0098	-0.0183***	-0.0038	-0.0226**	-0.0173**
	(0.0056)	(0.0105)	(0.0060)	(0.0079)	(0.0103)	(0.0069)
Pre-BTB Mean	0.856	0.783	0.864	0.674	0.708	0.712
N	1,079,393	160,140	447,724	688,171	155,596	265,834
Ln(Wage)	-0.0184	-0.0730	-0.0140	-0.0355**	-0.0560**	-0.0247
	(0.0158)	(0.0501)	(0.0181)	(0.0153)	(0.0224)	(0.0177)
Pre-BTB Mean	33820.36	23331.86	28125.04	22054.52	20348.27	21150.54
N	1,100,185	197,987	455,267	716,738	175,240	281,646
Aged 35-64						
Employment	-0.0042	-0.0131**	-0.0051	-0.0048	-0.0080**	-0.0044
	(0.0044)	(0.0057)	(0.0047)	(0.0031)	(0.0039)	(0.0046)
Pre-BTB Mean	0.941	0.882	0.936	0.947	0.902	0.916
N	3,024,397	392,895	696,409	2,459,942	419,500	519,010
Full-time Hours	-0.0056***	-0.0188***	-0.0093**	0.0009	-0.0110	-0.0085
	(0.0021)	(0.0039)	(0.0038)	(0.0044)	(0.0073)	(0.0057)
Pre-BTB Mean	0.914	0.878	0.905	0.746	0.805	0.747
N	2,847,891	346,618	652,709	2,331,010	378390	476,586
Ln(Wage)	-0.0172**	-0.0447**	-0.0253**	-0.0091	-0.0276*	0.0015
	(0.0085)	(0.0191)	(0.0125)	(0.0093)	(0.0139)	(0.0129)
Pre-BTB Mean	57846.1	40924.86	42018.05	35691.76	32987.62	28905.44
N	2,919,432	389,904	646,423	2,529,810	416,557	485,021

Notes: Based on the American Community Survey data. The estimates are obtained with a two-way fixed effects OLS model. The dependent variables are binary variables for employment and full-time employment and the natural logarithm of wages. See Section 3.2 for a list of controls. The table reports the pre-BTB mean of wages instead of the logarithm of wages.

* statistically significant at the 10% level; ** at the 5% level, *** at the 1% level

Table A.4. BTB and Employment Outcomes among Individuals with a College Degree

	Men			Women		
	White	Black	Hispanic	White	Black	Hispanic
Employment	-0.0007	-0.0026	-0.0014	-0.0014	0.0023	-0.0045
	(0.0020)	(0.0049)	(0.0045)	(0.0018)	(0.0039)	(0.0037)
Pre-BTB Mean	0.969	0.940	0.958	0.970	0.945	0.952
N	3,603,005	231,866	297,443	3,505,955	348,797	330,468
Full-time Hours	0.0002	-0.0057	-0.0115**	0.0108***	-0.0023	0.0029
	(0.0013)	(0.0039)	(0.0055)	(0.0033)	(0.0039)	(0.0061)
Pre-BTB Mean	0.908	0.901	0.916	0.778	0.868	0.823
N	3,491,193	218,006	285,034	3,403,543	329,766	314,930
Ln(Wage)	0.0053	-0.0284*	-0.0089	0.0247***	-0.0167	0.0145
	(0.0069)	(0.0169)	(0.0157)	(0.0083)	(0.0139)	(0.0186)
Pre-BTB Mean	101068	67875.42	76488.09	59329.51	54575.85	52416.8
N	3,244,764	213,337	272,073	3,282,159	328,518	309,721

Notes: Based on the American Community Survey data. The estimates are obtained with a two-way fixed effects OLS model. The dependent variables are binary variables for employment and full-time employment and the natural logarithm of wages. See Section 3.2 for a list of controls. The table reports the pre-BTB mean of wages instead of the logarithm of wages.

* statistically significant at the 10% level; ** at the 5% level, *** at the 1% level

Table A.5. BTB Laws and Employment Outcomes among Individuals without a College Degree: CPS Analysis

	Men			Women		
	White	Black	Hispanic	White	Black	Hispanic
Employment:	0.0031	-0.0259**	-0.0049	-0.0025	-0.0187	0.0062
	(0.0037)	(0.0111)	(0.0051)	(0.0027)	(0.0140)	(0.0053)
Pre-BTB Mean	0.934	0.862	0.921	0.941	0.883	0.909
N	2,385,346	332,584	656,231	1,861,329	359,544	446,590
Full-time hours	0.0051	0.0049	-0.0109**	-0.0004	-0.0209	-0.0107
	(0.0045)	(0.0090)	(0.0051)	(0.0058)	(0.0151)	(0.0109)
Pre-BTB Mean	0.891	0.873	0.905	0.726	0.803	0.759
N	2,009,554	263,324	560,734	1,614,922	297,736	380,666
Ln(Wage)	-0.0050	-0.0878**	-0.0622**	-0.0262	-0.1110***	-0.0263
	(0.0180)	(0.0370)	(0.0249)	(0.0164)	(0.0375)	(0.0382)
Pre-BTB Mean	52326.88	39174.02	37842.04	32021.42	30056.53	26215.2
N	212,100	38,976	93,521	173,871	44,220	66,170

Notes: Based on the Current Population Survey data. The estimates are obtained with a two-way fixed effects OLS model. The dependent variables are binary variables for employment and full-time employment and the natural logarithm of wages. See Section 3.2 for a list of controls. The table reports the pre-BTB mean of wages instead of the logarithm of wages.

* statistically significant at the 10% level; ** at the 5% level, *** at the 1% level