Estimating the Effect of State-Level Involuntary Commitment Laws on Substance Use Outcomes

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Abstract:

Substance abuse remains a persistent crisis in the United States, prompting some states to implement involuntary commitment laws for the compulsory treatment of individuals with substance use disorders. This study estimates the impact of these laws on treatment utilization and substance use mortality rates using a comprehensive dataset and a difference-in-differences approach, comparing trends between states with and without such statutes.

Findings reveal an inconsistent picture across treatment states. Some states experienced declines in overall and court-mandated treatment admissions post-implementation, while others saw rises in criminal justice referrals. Effects on substance use mortality were mixed, with some states showing increases in drug overdose deaths despite the laws. The pooled analysis suggests an increase in drug overdose rates, but this should be interpreted cautiously due to the exclusion of states violating parallel trends assumptions. A crucial limitation is the lack of data on how these laws are implemented in practice, constraining the conclusions that can be drawn.

Results underscore the need for rigorous policy monitoring and evaluation to better understand the tradeoffs of this controversial policy lever. More empirical work is needed to determine if and under what circumstances involuntary treatment can effectively address the ongoing drug crisis while preserving civil liberties.

Introduction:

Substance abuse in the United States has had far-reaching consequences for individuals, families, and communities. According to the National Survey on Drug Use and Health (NSDUH), an estimated 46.8 million Americans aged 12 or older had a substance use disorder in 2022, including 29.4 million people with an alcohol use disorder and 27.2 million people with a drug use disorder (Substance Abuse and Mental Health Services Administration). The economic burden of substance abuse is staggering, with costs related to healthcare, lost productivity, and criminal justice involvement totaling over $400 billion annually (US Department of Health and Human Services). The opioid epidemic, in particular, has devastated communities across the country, with the rise of illicit fentanyl contributing to a surge in overdose deaths in recent years (National Institute on Drug Abuse).

In response to this crisis, some states have implemented involuntary treatment laws that allow for the compulsory commitment of individuals with severe substance use disorders. These laws are based on the principle that, in certain cases, the state has a duty to intervene and protect individuals from the harmful consequences of their substance abuse, even if it means overriding their autonomy. Proponents argue that involuntary treatment can save lives, reduce the societal harms associated with untreated addiction, and provide a pathway to recovery for individuals who may not otherwise seek help (Psychiatric Services 2018).

However, the use of involuntary commitment for substance abuse remains controversial, with civil liberties advocates raising concerns about the potential infringement on individual rights and the lack of due process. Critics argue that compulsory treatment violates the principles of self-determination and bodily integrity, and that the decision to seek treatment should be a personal choice (Beletsky 2018). There are also questions about the effectiveness of involuntary treatment, with some studies suggesting that coerced treatment may be less successful than voluntary treatment in promoting long-term recovery (Werb et al. 2016).

Despite the ongoing debates, there has been limited empirical research on the impact of involuntary treatment laws on substance abuse outcomes at the population level. A study in the American Journal of Drug and Alcohol Abuse found that states with involuntary commitment laws for substance abuse had improved drug outcomes in the first week after release from treatment (Strauss & Falkin, 2001). However, the study did not examine the long term effects and was limited in geographical scope. Other research has focused on the impact of involuntary treatment on criminal recidivism rates (Hiller et al. 2006) or the legal and ethical dimensions of these laws (Laureano et al. 2024), but there remains a gap in understanding their broader public health impacts.

This study aims to address this gap by estimating the effects of state involuntary commitment laws for substance abuse on treatment utilization and substance use mortality outcomes. We draw on a comprehensive dataset compiled from multiple sources, including the Treatment Episode Data Set (TEDS-A) for treatment admissions, the CDC WONDER database for overdose and alcohol-related deaths, and the U.S. Census Bureau for population estimates. Our analysis covers all fifty states over the period from 1999 to 2021. Six states implemented involuntary treatment laws during this timeframe.

To isolate the causal impact of these laws, we employ a difference-in-differences (DiD) approach, which compares changes in outcomes pre- and post-law implementation in treatment states to changes over the same period in control states. This quasi-experimental design allows us to control for both time-invariant differences between states and common time trends that may affect substance use outcomes. By leveraging variation in the timing of law implementation across states, we can identify the average treatment effect of these policies while accounting for potential confounding factors.

The remainder of this report is structured as follows: In the Methods section, we provide a detailed description of our data sources, sample selection criteria, and analytical approach. The Results section presents our key findings, including descriptive statistics and estimates from our DiD models. We then interpret these results and discuss their implications in the Discussion section, before concluding with a summary of our main takeaways and suggestions for future research.

Our study contributes to the limited evidence base on the effectiveness of involuntary treatment laws as a policy tool for addressing the ongoing substance abuse crisis. By providing a rigorous empirical analysis of the population-level impacts of these laws, we aim to inform the ongoing debates and guide policymakers in their efforts to develop evidence-based strategies for reducing the harms associated with substance abuse. At the same time, we acknowledge the limitations of our approach (detailed in the Discussion and Conclusion sections) and the need for further research to fully understand the complex interplay between involuntary treatment, individual rights, and public health outcomes.

Methods:

Data Sources:

Our analysis relies on a comprehensive dataset compiled from multiple sources. We obtained treatment center admissions data from the Substance Abuse and Mental Health Services Administration's Treatment Episode Data Set (TEDS-A). The TEDS-A dataset provides information on admissions to substance abuse treatment facilities by state, referral type, drug type, and other characteristics. We used data spanning from 2005 to 2021, which was provided in separate files for each year or range of years (2005-2009, 2010-2014, 2015-2019, 2020, and 2021). Drug overdose and alcohol-related mortality data from 1999-2021 were sourced from the CDC WONDER database, which contains detailed cause-of-death information for all U.S. states and counties. Additional population estimates used to calculate per capita rates were obtained from the U.S. Census Bureau's Vintage dataset.

To determine which states have implemented involuntary treatment laws and when these laws came into effect, we conducted a review of state legislative databases and consulted with individuals at state departments of behavioral health or the equivalent agency. Based on this review, we identified six states that have passed such laws between 1999 and 2021, which form our treatment group. Twelve states have no mechanism for the involuntary commitment of drug and alcohol abusers. With the exception of Oregon, which is missing treatment admissions data from 2015 onwards, these states serve as our control group. Of note, too, is that while New York and New Jersey technically don't have explicit involuntary treatment laws, there are other legal mechanisms by which individuals can be committed (New York State Office of Mental Health). As a result, these two states were dropped from the control group.

Data Cleaning:

The separate TEDS-A files were combined into a single dataset using the `bind_rows()` function from the `dplyr` package in R. Relevant variables for analysis were selected, including admission year, age, gender, race, education, living arrangement, state FIPS code, referral source, treatment service, criminal referral, and primary substance. These variables were renamed for clarity and consistency.

The CDC overdose data underwent several cleaning steps. Columns were renamed for better readability, and leading or trailing double quotes were removed using the `gsub()` function. Rows with missing or empty state names were filtered out. The CDC data was then reshaped using the `pivot_wider()` function from the `tidyr` package, creating separate columns for drug-induced and alcohol-induced deaths and death rates, with each state-year combination as a single row.

Linear interpolation was used to estimate missing treatment admissions data for Alabama in 2007. The indices for the years 2006, 2007, and 2008 were identified, and the average of the 2006 and 2008 values was calculated to impute the missing 2007 data. This interpolation was applied to the total admissions, criminal referral admissions, and court-mandated admissions variables to minimize the impact of the missing data on the analysis. The data is likely missing due to the fact that when states do not report sufficient data, TEDS-A excludes the data from that year from the dataset. It is highly unlikely that interpolating one year's worth of admissions data for one state would have an impact on overall treatment-related findings, but further work could nevertheless involve a sensitivity analysis to consider the impact of this decision.

Data aggregation and summarization were performed to prepare the data for analysis. Using the `group_by()` and `summarize()` functions from the `dplyr` package, total admissions, criminal referral admissions, court-mandated admissions, and non-ambulatory admissions were calculated for each state and year combination in the TEDS-A dataset.

The TEDS-A and CDC datasets were merged with the `left_join()` function from the `dplyr` package, matching on the state name and year variables. The resulting merged dataset was used for the subsequent DiD analysis, as described in the Statistical Analysis section.

Measures:
Our primary outcomes of interest are:

- **Treatment center admissions rate**: Total admissions to substance abuse treatment facilities per 100 thousand population.
- **Treatment center admissions via criminal referral rate**: Total admissions via criminal referrals to substance use treatment facilities. In the TEDS-A dataset, criminal referrals are described as follows: "Any police official, judge, prosecutor, probation officer or other person affiliated with a federal, state, or county judicial system. Includes referral by a court for DWI/DUI, clients referred in lieu of or for deferred prosecution, or during pre-trial release, or before or after official adjudication. Includes clients on pre-parole, pre-release, work or home furlough or Treatment Accountability for Safer Communities

(TASC). The client need not be officially designated as ‘on parole.’ Includes clients referred through civil commitment.”

- **Treatment center admissions via court referral rate**: Total admissions via criminal referrals through the court system. Under the umbrella of criminal referrals, court referrals describe criminal justice referrals to treatment centers that came by way of federal, state, or other courts. Given that involuntary commitments tend to require a court hearing, this metric serves as a potential proxy for the number of involuntary treatment admissions.
- **Drug overdose mortality rate**: Deaths due to drug overdose per 100 thousand population.
- **Alcohol-related mortality rate**: Deaths due to alcohol-related causes per 100 thousand population.

Statistical Analysis:

To estimate the effect of involuntary treatment laws on our outcomes of interest, we employ a difference-in-differences (DiD) design. This approach compares changes in outcomes pre- vs. post-law implementation in treatment states to changes over the same time period in control states. The key identifying assumption is that in the absence of the laws, trends in the treatment and control groups would have been parallel.

We employed linear regression models for the DiD analysis, which is a common approach in health policy literature (Roth et al. 2023; Zhou et al. 2016; Health Policy Data Science Lab). The use of linear models assumes that the treatment effect is constant over time and across units, and that the outcomes are normally distributed with equal variances across groups. Given that we are working with state-level aggregated data over multiple years, it is reasonable to assume that the central limit theorem applies, which suggests that the distribution of the outcome variables would approach normality, even if the individual-level data might not be normally distributed.

To assess the equal variances assumption (homoscedasticity), we visually inspected the residual plots from our DiD models. If the residuals appear to have a relatively constant spread across the range of fitted values, it suggests that the equal variances assumption is not severely violated. Based on the residual plots, we found that the equal variances assumption was not severely violated for most outcomes. For each of our treatment states, the residuals for the Total_Admissions_Rate (Figure 1), Alcohol_Death_Rate, Drug_Death_Rate and Criminal_Referral_Rate outcomes exhibited a relatively constant spread across the range of fitted values. The residuals for Court_Mandated_Rate likewise exhibited a relatively constant spread, except for Maine (Figure 2) and Washington, where the outcomes showed a clear pattern.

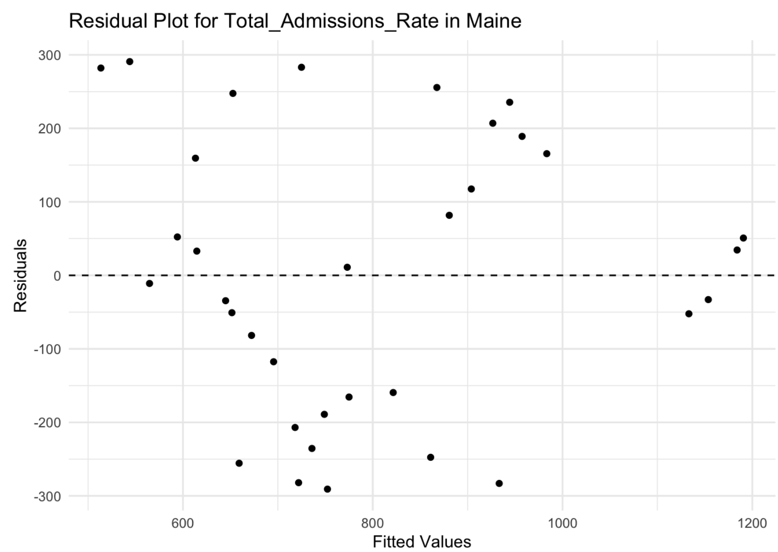

Figure 1: Residual plot for Maine's total admissions rate

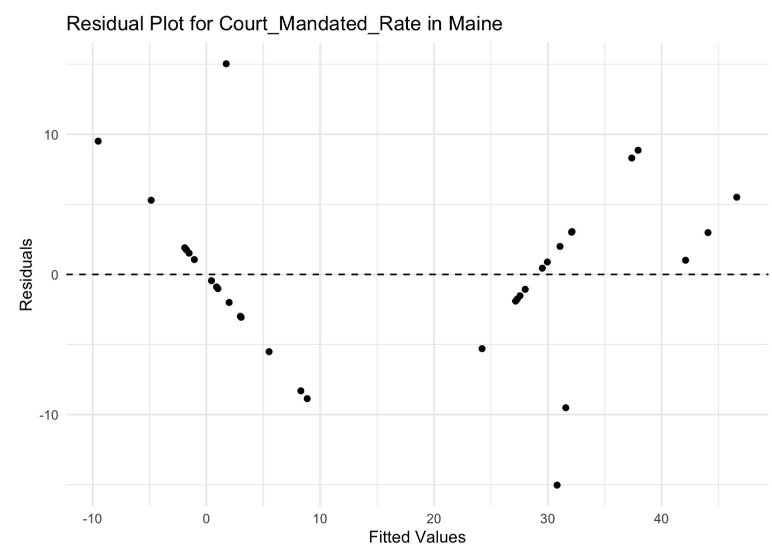

Figure 2: Residual plot for Maine's court mandated admissions rate

Before estimating the DiD models, we also conducted a pre-treatment trends analysis to verify the parallel trends assumption. For each outcome and treatment state, we estimated a regression model using only the pre-treatment period data, with the outcome variable as the dependent variable and group indicators (treatment and control), time trends, and their interaction as independent variables. If the interaction term was statistically significant ($p < 0.05$), we considered the parallel trends assumption to be violated for that particular outcome and state.

In cases where the parallel trends assumption was violated, we excluded the corresponding state from the DiD analysis for that specific outcome. This approach ensures that the DiD estimates are not biased by differential pre-treatment trends between the treatment and control groups.

For the pooled DiD model, which combines all treated states, we first identified the states that violated the parallel trends assumption for each outcome. We then excluded these states from the pooled analysis for the respective outcomes. By doing so, we aimed to obtain a more reliable estimate of the average treatment effect across states that satisfied the parallel trends assumption.

In addition to the parallel trends assumption, the stable unit treatment value assumption (SUTVA) is another important consideration in DiD analysis. SUTVA requires that the treatment status of one unit does not affect the potential outcomes of other units, and that there are no spillover effects between treated and untreated units. In the context of our study, SUTVA implies that the implementation of involuntary treatment laws in one state does not influence the outcomes in other states. Given the state-level nature of these laws and the relatively independent operation of state-level health systems, it is reasonable to assume that SUTVA holds in this case. However, we acknowledge the possibility of minor spillover effects, such as cross-state patient transfers or information sharing between states, which could potentially violate SUTVA to some extent.

We estimate DiD models of the following form:

$$Y_{st} = \beta_0 + \beta_1(Treat_s \times Post_t) + \alpha_s + \gamma_t + \varepsilon_{st}$$

Where:
- Y_{st} is the outcome of interest for state s in time t.
- β_0 is the intercept.
- β_1 is the coefficient of interest, representing the DiD estimate of the treatment effect.
- $Treat_s$ is a binary indicator that equals 1 if state s is in the treatment group, and 0 otherwise.
- $Post_t$ is a binary indicator that equals 1 for the period after the treatment starts, and 0 for the period before the treatment.
- α_s represents state-specific fixed effects, capturing unobserved, time-invariant characteristics of each state.
- γ_t represents time-specific fixed effects, capturing common shocks across all states in each time period.
- ε_{st} is the error term, representing unobserved factors that affect Y for each state at each time point.

We estimate separate models for each outcome and for each treatment state individually, excluding states that violate the parallel trends assumption for the specific outcome. In addition, we estimate a pooled model that combines all treated states and assesses the average effect of the laws, again excluding states that violate the parallel trends assumption for each outcome.

Standard errors are clustered at the state level to account for serial correlation. All analyses were conducted in R version 2023.03.0+386, using the fixest package for estimating the DiD models.

Results:

Trends in Treatment Admissions:

Visual inspection of the trends in nationwide per capita treatment admissions reveals considerable heterogeneity across states (Figure 3). In general, between 2005 and 2021, treatment admission rates declined from their peak in 2009 until 2014. Rates increased from 2014 to 2018, and then fell once again from 2018 to 2021. The overall trend is a moderate decline from 2005 to 2021 (Figure 4).

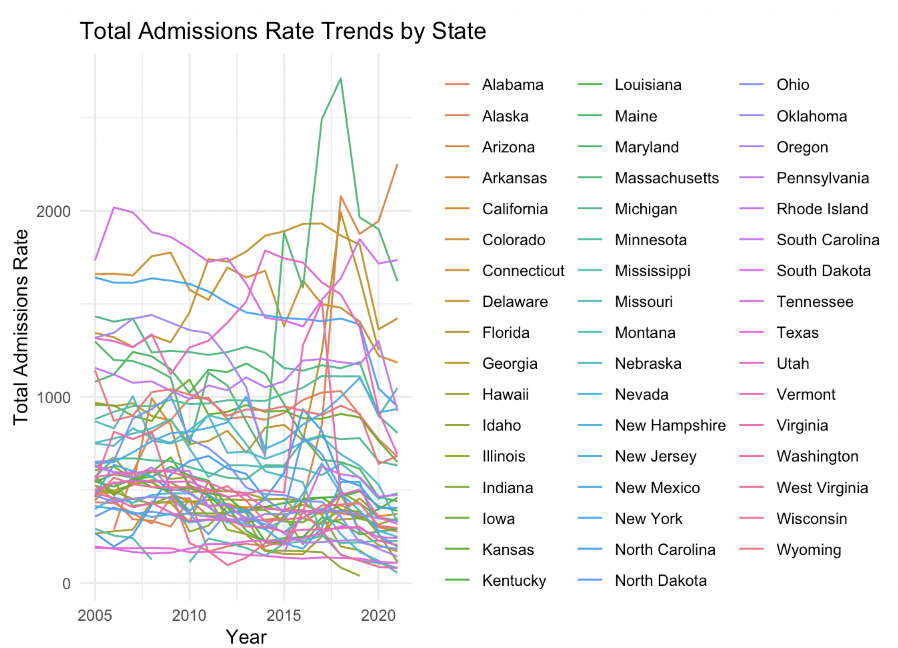

Figure 3: Nationwide admissions rate trends

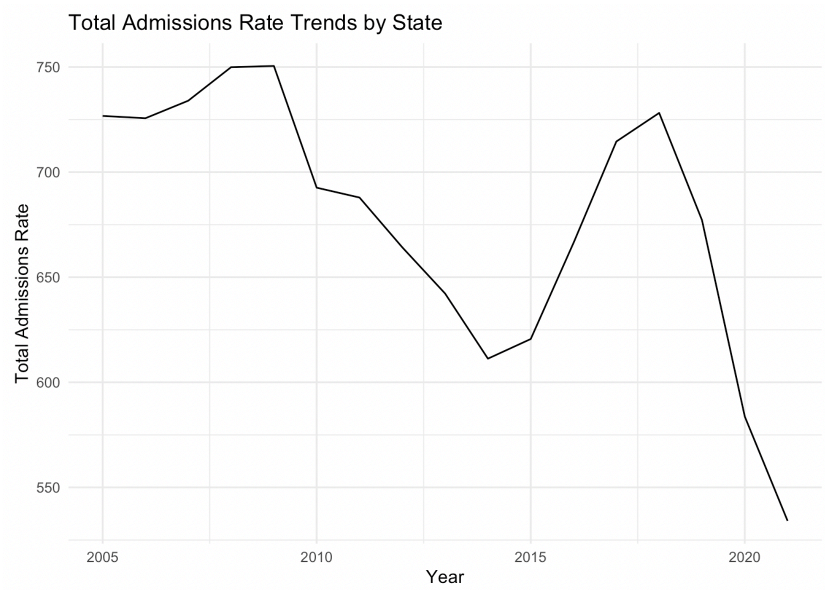

Figure 4: Pooled national admissions trend

Within the treatment group, some states like Ohio and Maine experienced declines following law implementation, while others like Michigan and Indiana exhibited more modest changes against relatively stable trends in the control group (Figure 5).

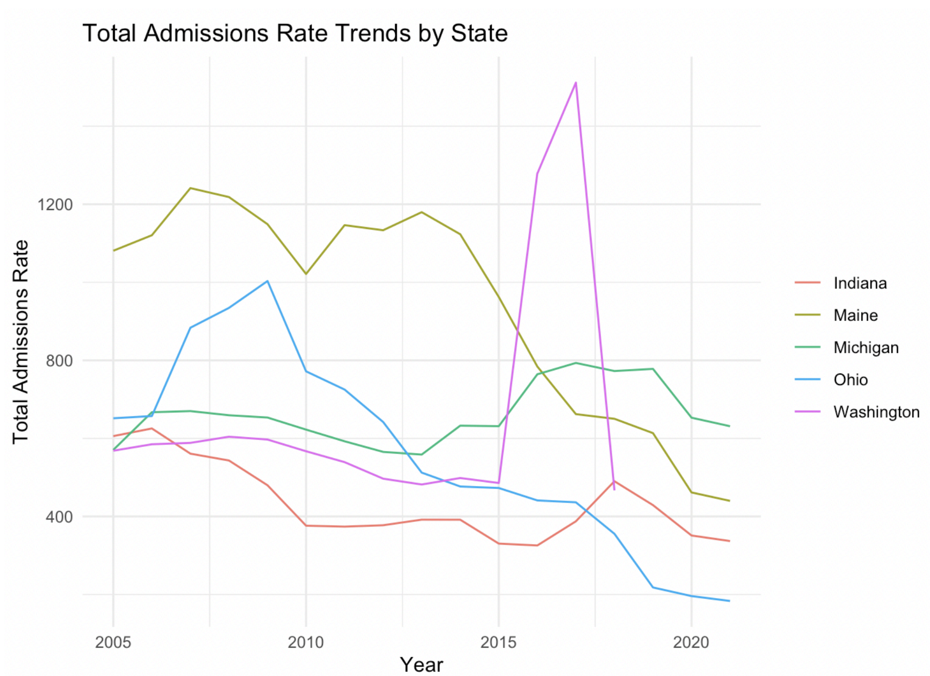

Figure 5: Admissions trends in select treatment states

The difference-in-differences (DiD) regression results corroborate these divergent patterns. We find statistically significant declines in total treatment admissions in Indiana (-306 per 100,000,

$p<0.001$) and Ohio (-490 per 100,000, $p<0.001$) relative to the control group following law passage. However, the estimates for Michigan (-58 per 100,000) and the pooled treatment effect (-307 per 100,000) are not statistically distinguishable from zero at conventional levels.[1]

Court-Mandated and Criminal Justice Referrals

Court-mandated treatment admissions for most treatment states remain very low from 2005-2021, possibly indicating underreporting of this specific admission statistic in the TEDS-A dataset. The one exception is Ohio, which exhibits a pronounced drop from 2008 onwards. These visual impressions are borne out in the regression analyses, which detect significant declines in court admissions for Ohio (-153 per 100,000) following involuntary treatment law implementation.

In contrast, Michigan experienced a statistically significant increase of 28 court admissions per 100,000 population ($p<0.001$). Pooling across treatment states, however, yields a negative but insignificant effect on court admissions (-25 per 100,000).

The patterns are more mixed for criminal justice referrals to treatment. While Washington saw a large significant drop (-202 per 100,000, $p<0.001$), Ohio's decline was more modest (-119 per 100,000, $p<0.01$). Michigan recorded a significant increase of 27 per 100,000 ($p<0.05$). The pooled treatment effect of -59 per 100,000 is negative but not statistically distinguishable from zero.

Substance Use Mortality

Turning to substance use mortality outcomes, we find mixed effects of involuntary treatment laws on drug overdose rates. Delaware experienced a significant increase of 5.5 per 100,000 ($p<0.01$) relative to control states post-implementation. Michigan's positive point estimate (+0.77 per 100,000) is not significantly different from zero. However, the pooled treatment effect of 3.0 per 100,000 ($p<0.001$), excluding states that violate the parallel trends assumption[2], suggests a significant increase in drug overdose rates following involuntary treatment law implementation. This finding is inconsistent with the intended effect of these laws and warrants further investigation.

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[1] The parallel trends assumption was violated for Maine and Washington, suggesting that their pre-treatment trends in total admissions differed significantly from the control group. As a result, the DiD estimates for these states (Maine: -331 per 100,000, $p<0.05$; Washington: -635 per 100,000, $p<0.001$) should be interpreted with caution and are not included in the main discussion.

[2] The parallel trends assumption was violated for drug overdose rates in Indiana, Washington, and Ohio, suggesting that their pre-treatment trends differed significantly from the control group. As a result, the DiD estimates for these states (Indiana: +2.2 per 100,000, $p<0.05$; Washington: -8 per 100,000, $p<0.001$; Ohio: +11 per 100,000, $p<0.001$) should be interpreted with caution and are not included in the main discussion or the pooled treatment effect.

The effects on alcohol-related mortality rates are also mixed. We estimate a significant decrease for Delaware (-1.5 per 100,000, $p<0.05$) and a modest decline for Michigan (-0.55 per 100,000, $p<0.05$). The pooled treatment effect of +0.23 per 100,000, excluding states that violate the parallel trends assumption[3], is positive but not statistically differentiable from zero.

Outcome	Indiana	Ohio	Michigan	Maine	Washington	Delaware	Pooled
Total Admissions	-306.5***	-490.0***	-58.1	-	-	-	-86.2
	(47.8)	(118.9)	(64.6)				(122.2)
Court-Mandated Admissions	22.8***	-152.7***	27.8***	12.0	-	-	-30.0
	(5.6)	(31.3)	(4.4)	(7.0)			(40.3)
Criminal Justice Referrals	-	-118.9**	27.0*	-91.4***	-201.9***	-	-60.9
		(35.0)	(11.3)	(17.0)	(5.9)		(41.5)
Drug Overdose Mortality	-	-	0.77	2.3	-	5.5**	3.0***
			(1.1)	(1.2)		(1.5)	(0.80)
Alcohol-Related Mortality	1.3***	-	-0.55*	1.3*	-	-1.5*	-0.27
	(0.15)		(0.25)	(0.54)		(0.61)	(0.67)

Table 1: Difference-in-difference results for each state and outcome of interest[4]

In sum, we find relatively consistent evidence of reductions in overall and court-mandated treatment admissions across several states following involuntary treatment law implementation. The pooled analysis suggests a significant increase in drug overdose rates, although this finding should be interpreted with caution due to the exclusion of several states that violated the parallel trends assumption. Impacts on criminal justice referrals and alcohol-related mortality present a more uneven picture, with some states exhibiting significant changes despite the laws. These divergent patterns likely reflect broader underlying trends as well as differences in how vigorously the policies were implemented and other unobserved factors across states.

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[3] The parallel trends assumption was violated for alcohol-related mortality rates in Washington and Ohio. Consequently, the DiD estimates for these states (Washington: +0.39 per 100,000, not statistically significant; Ohio: -0.22 per 100,000, not statistically significant) should be interpreted with caution and are excluded from the main discussion and the pooled treatment effect. Additionally, while Maine did not violate the parallel trends assumption, its significant increase (+1.3 per 100,000, $p<0.05$) is not included in the main discussion for consistency with the drug overdose rate section.

[4] Each cell reports the difference-in-differences coefficient estimate with standard errors clustered by state in parentheses.
Significance levels: * $p<0.05$, ** $p<0.01$, *** $p<0.001$.
The pooled analysis excludes states that violate the parallel trends assumption for each outcome.
Individual state results that violated the parallel trends assumption are indicated by a dash (-) and are not reported.

Discussion:

This study aimed to estimate the effects of state involuntary commitment laws for substance abuse on treatment utilization and substance use mortality outcomes. Our findings highlight the challenges of rigorously evaluating policies that appear to be inconsistently implemented and tracked across jurisdictions.

While we document declines in overall and court-mandated treatment admissions in several states like Indiana and Ohio following law passage, the patterns are uneven. Moreover, the effects on criminal justice referrals and substance use mortality present a mixed picture, with some states exhibiting increases in overdose deaths despite the laws. Notably, the pooled analysis suggests a significant increase in drug overdose rates, although this finding should be interpreted with caution due to the exclusion of several states that violated the parallel trends assumption. This unexpected result raises questions about the effectiveness of involuntary treatment laws in reducing substance use-related harms and highlights the need for a more rigorous evaluation of these policies.

The observed trends in treatment admissions should be considered within the broader context of the opioid epidemic and related policy changes during the study period. The overall decline in admission rates from 2009 to 2014 coincides with the introduction of abuse-deterrent formulations for prescription opioids and increased efforts to reduce opioid prescribing (Cicero & Surratt 2012). The subsequent increase from 2014 to 2018 may reflect the growing prevalence of illicit fentanyl and the implementation of Medicaid expansion under the Affordable Care Act, which improved access to substance use disorder treatment (Lyon et al. 2014). The renewed decline from 2018 to 2021 could be attributed to the disruptions caused by the COVID-19 pandemic, which limited access to healthcare services and altered patterns of substance use.

The divergent patterns observed across states in the treatment group may be explained by differences in the implementation and enforcement of involuntary treatment laws. States with more robust enforcement mechanisms and resource allocation for involuntary treatment may have experienced greater declines in admissions compared to those with weaker implementation. Additionally, state-specific factors such as the availability of alternative treatment options, public awareness of the laws, and the capacity of the treatment system could have influenced the impact of these laws on admissions.

Our outreach to state behavioral health departments revealed that many do not systematically collect data on if and how their involuntary commitment statutes are actually operationalized. This, combined with prior research (Christopher et al. 2015) documenting the underutilization of involuntary treatment provisions, raises the possibility that the laws exist on the books in name only, without meaningful enforcement or impacts on the ground in some jurisdictions. The wide variation in our estimates likely reflects these disparities in real-world policy implementation.

The positive impacts on overdose mortality observed in several states and the pooled analysis seem to contradict the premise that compulsory treatment should reduce the harms of substance abuse. While concerning, these findings could partly arise from broader confounding trends in substance use that differentially affected states over the study period. Our difference-in-differences approach aims to account for such violations of the parallel trends assumption, but cannot fully do so.

The inconsistencies in alcohol-related mortality outcomes across states may be due to several factors. First, involuntary treatment laws are primarily targeted at individuals with severe substance use disorders, particularly those involving illicit drugs. As a result, the impact on alcohol-related mortality may be less direct or pronounced. Second, alcohol use disorders often co-occur with other mental health conditions, which may require a more comprehensive treatment approach beyond involuntary commitment. Finally, sociocultural factors and state-level alcohol policies (e.g., taxes, availability) could have influenced alcohol-related mortality rates independently of involuntary treatment laws.

From a civil liberties perspective, indiscriminately applying involuntary treatment policies with limited evidence for their role in reducing drug overdose rates would represent an unacceptable tradeoff. At minimum, our results highlight the need for states to rigorously monitor policy implementation and track key outcome metrics if they elect to pursue this strategy for combating substance abuse.

The inconsistent framing and limited data available on involuntary commitment severely circumscribe the definitive conclusions we can draw from this study. Several future research directions could help overcome these limitations:

1) Complementary qualitative investigations of how involuntary processes actually unfold across state jurisdictions that could identify specific implementation practices impacting effectiveness.

2) Surveys or audits directly assessing the degree to which state laws are actively utilized, and what factors predict prioritization.

3) Simulation studies disentangling the scale and compositional effects of involuntary treatment on population outcomes from confounding trend violations.

4) Enhanced data infrastructure and transparency requirements around involuntary commitment to support rigorous evaluation in jurisdictions electing to implement such policies.

Ultimately, more empirical work is critically needed to understand if, how, and under what circumstances involuntary treatment can be an effective tool in addressing the ongoing drug crisis. While our study represents an initial effort at evaluating population-level impacts, issues around data availability and policy implementation consistency severely limit the conclusions that can be drawn. We hope these findings catalyze efforts to boost monitoring and evaluation pipelines to better understand the tradeoffs of this controversial but potentially important policy lever.

Conclusion:

This study represents an initial attempt to evaluate the population-level impacts of state involuntary commitment laws for substance abuse on treatment utilization and overdose mortality. Our findings reveal an inconsistent picture across states that have enacted such policies, with some experiencing declines in treatment admissions but rises in overdose deaths post-implementation. These unexpected results underscore the need for careful monitoring and evaluation of these laws to ensure they are not inadvertently contributing to substance use-related harms.

A crucial limitation in our study is the lack of comprehensive data on whether and how these laws are implemented in practice. With many states not systematically tracking involuntary commitments, the laws may exist in name only across several jurisdictions. This dearth of monitoring data severely constrains the conclusions that can be drawn. In addition, states keep imperfect records of each admission to treatment facilities. In many cases, for example, whether or not an individual was referred to a treatment facility via a criminal or voluntary referral was not recorded. In this way, variations in "admissions" may be better understood as variations in recordkeeping. Finally, many states passed involuntary treatment laws in the 1970s and 1980s – but our data does not span back that far, thus making it impossible to include these states in our DiD analyses.

Broadly, this study underscores the challenges of empirically disentangling the impacts of policies targeting personal behaviors amid the complexities of substance use disorders. The inconsistent findings across states highlight how the real-world effects of involuntary commitment laws are shaped by a myriad of contextual factors, from the details of policy implementation to the broader social and economic determinants of health. Overcoming these knowledge gaps will require multidisciplinary approaches that blend rigorous data monitoring and statistical evaluation with qualitative examinations of how policies unfold in real-world contexts. Only through such comprehensive efforts can we develop evidence-based strategies to address the drug crisis while preserving individual civil liberties.

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