# The Societal Effects of Harm Reduction

*By*

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## Dedication

This dissertation is dedicated to my child, Silas Edgerton who has consistently tolerated the past four years and been my largest champion.

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## ABSTRACT

My dissertation consists of three chapters. The first chapter investigates the impact of syringe service program (SSP) legislation on fatal and nonfatal overdoses in Tennessee. Leveraging a 2018 law I utilize a difference-in-differences model using SSPs as a proxy for naloxone distribution. I find a significant increase in the gross number of overdoses in counties that implemented an SSP but not in the rate of overdoses in those counties. The second chapter examines the effect of SSP legislation on county-level crime. Many opponents of SSPs and harm reduction in general use “Not in my backyard” as an argument suggesting that these social services increase crime and drug use. I use a recent Tennessee law legalizing SSPs to identify if they do in fact increase crime. I find that implementation of SSPs does not have a significant effect on crime. The third chapter studies the effects of a federal regulation on sodium permanganate, an ingredient in the manufacturing of cocaine, on illicit drug use and overdose deaths, finding a significant increase in heroin use after the regulation but no other significant effects of illicit drug use or mortality.

# Chapter 1

# The Effects of Syringe Service Programs on Overdose Deaths in Tennessee

## 1.1 Introduction

Opioid use, including heroin, prescription painkillers, and, most recently, fentanyl, has become a public health crisis throughout the United States (Scholl et al. 2019). In 2020 alone, more than 68,000 deaths were attributed to opioid use, nearly nine times as many deaths as in 1999 (CDC 2020) and a 46% increase from 2018 (NIDA 2023). While many interventions have been conducted to help reduce this number, including the expansion of naloxone, an overdose prevention medication, the introduction of fentanyl test strips, and an increase in linkage to substance use disorder treatment, the number of overdoses continues to increase yearly.

People who inject drugs are at increased risk for bloodborne pathogens, mainly HIV and Hepatitis C (HCV). Of the nearly 38,000 new HIV diagnoses in 2018, people who inject drugs accounted for over 10% of those while only accounting for 1.5% of the U.S. adult population (Bradley et al. 2023). Further, it is estimated that more than half of people who currently or formerly injected drugs have an HCV infection (Gicquelais et al. 2019).

Harm reduction services intend to reduce the risk of overdose and infectious disease while increasing the quality of life for people who inject drugs. Interventions such as increased HIV and HCV testing and linkage to treatment, the introduction of fentanyl test strips, distribution of naloxone, and syringe services programs (SSPs) to distribute sterile syringes and cookers to people who inject drugs have been recently gaining traction throughout the United States. SSPs have been shown to be efficacious worldwide at decreasing HIV and HCV risk among people who inject drugs, with estimates of a 58% reduction in HIV incidence among people who inject drugs (Bushling et al. 2021, Vidourek et al. 2019). However, many opponents of SSPs argue that they enable drug use and increase drug abuse (Sharma 2019). Initially designed to prevent the spread of infectious disease, SSPs have recently begun to be hubs of harm reduction services and often distribute naloxone, fentanyl test strips, and other forms of drug testing.

In 2018, Tennessee began allowing the legal operation of SSPs with the approval of the Department of Health (TDH). Specifically, the law allows for organizations to obtain TDH approval to provide sterile syringes to individuals 1,000 feet away from a school or park (2,000 feet in rural areas). For clients of SSPs, they are criminally and civilly protected from liability for possession of syringes and residual amounts of controlled substances used in syringes or injection equipment as long as they are either actively at the SSPs or in transit to or from the SSP. Beyond sterile syringes and other injection equipment SSPs in Tennessee provide a myriad of other services including HIV and HCV testing, distribution of fentanyl test strips, direct linkage to substance abuse treatment, and distribution of naloxone, an overdose reversal medication. The distribution of naloxone is vital in SSPs roles at curtailing fatal overdoses throughout the state. While sterile injection supplies will reduce the spread of bloodborne pathogens, they do not directly reduce overdoses, however with more organizations distributing naloxone I hypothesize that this could have an effect on the number of overdoses. The direction of this effect, however, can be debated. The provision of sterile syringes lower health risks associated with injection drug use which in theory may induce a moral hazard effect therefore increasing the amount of drugs used or frequency of drug use. Similarly, the distribution of naloxone has been shown to induce moral hazard. Doleac and Mukherjee identified that expanding naloxone access laws resulted in an increase in opioid abuse and no reduction in opioid related mortality. These may potentially show that using SSPs as a proxy for naloxone distribution in fact increase drug overdoses.

Using data from TDH on legally operating SSPs throughout the state and the number of fatal and nonfatal overdoses at the county level, I conduct a difference-in-differences analysis and a randomization inference to identify the causal relationship between legal SSP operation and fatal and nonfatal drug overdoses in Tennessee.

In the next section, I will identify previous literature investigating SSPs and overdose. Section III will discuss the data that I use, where it was obtained, and the generalizability of it. Section IV will discuss the identification strategy. Section IV will show the results of the difference-in-difference and randomization inference analysis. Lastly, section V will finalize this paper with a discussion of the implications of this study, limitations, and future research needs surrounding harm reduction services.

## 1.2 Literature

To my knowledge, one study has looked directly at the effects of SSPs on drug overdose rates, while multiple have looked at the impact of SSPs on drug use behavior, and their potential to affect drug overdoses. This paper attempts to fill those gaps and identify the causal relationship between SSPs and overdoses.

In a recent study, Packham (2022) looks at the effects of SSPs on HIV diagnoses and drug-related deaths. The author finds a significant decrease in HIV rates and an increase in drug-related mortality, specifically in rural counties and counties that implemented an SSP after the influx of illicitly manufactured fentanyl. A decrease in HIV rates is expected, as SSPs have been shown to decrease the rate of HIV transmission. However, the increase in drug-related mortality contradicts much of the public health predictions. One possible explanation is differences in state policy environments and SSP regulations. Also, with the data from this paper being from 2009-2016, SSPs may have altered their approach in the wake of the increase in fentanyl in communities. Even with these explanations, this paper suggests that SSPs alone cannot prevent overdose and may increase drug-related mortality.

One study looked at former SSP participants at a methadone clinic in Seattle. Hagan et al. found that SSP use was associated with a reduction or cessation of injection drug use and increased drug treatment enrollment. Former SPP participants were five times more likely to begin methadone treatment and 60% more likely to be retained in care for one year.

A second study modeled the health benefits of many policy responses to the opioid epidemic, including prescribing, drug disposal, treatment access, and SSP access. Pit et al. estimated that SSP access did not affect the number of deaths associated with prescription drugs but reduced the number of deaths from heroin from 2016-2020 by 2700 deaths or 1.8%.

There is some evidence that access to naloxone has unintended effects. Using naloxone access laws, Google trend data on naloxone, other policies affecting people who use drugs (Good Samaritan, prescription drug monitoring board, etc.) the authors develop a robust database and utilize a DID to identify the causal effects of naloxone access laws on opioid related outcomes, identifying an increase in opioid abuse, opioid related crime and no decrease in opioid related mortality (Doleac and Mukherjee 2018).

## 1.3 Data

Syringe services programs in Tennessee have long been taboo. In 2018, however, a law was passed that allowed organizations to begin operating these programs with authorization granted through the Tennessee Department of Health. As of 2020, the most recent year of nonfatal overdose data, five counties had adopted an operational SSP. Davidson, Hamilton, and Knox began operating in 2018, while Shelby and Washington began in 2019. I obtained county-level overdose death data from the Tennessee Department of Health (TDH). The data covers all Tennessee residents who died of acute poisoning attributed to the use of substances (TDH 2023). I gathered county demographic information from IPUMS National Historical Geographic Information System. (NHGIS). NHGIS provides free online access to summary statistics and GIS files for the U.S. from

1790 through the present. Population data are collected through the decennial censuses and the American Community Survey (Manson et al 2022). State-licensed SSP data was obtained from the TDH, which grants licensure and oversees the operation of SSPs within Tennessee. This licensure is a measure of when an organization in a given county was given authorization to begin SSP operations. Unemployment data was acquired from the State of Tennessee Department of Labor and Workforce Development (T.N. Department of Labor and Workforce Development 2022).

Data from all 95 counties in Tennessee, including demographics, fatal overdose, nonfatal overdose, and if the county had a legal SSP in a given year, are used. Counties were treated as having an SSP if an organization within the county applied for and was granted licensure to operate within a given year. Five of the ninety-five counties were treated at some point in the study period. The outcomes of interest are county-level fatal and nonfatal overdoses. Overdoses are measured as the number of deaths per 100,000 individuals. County-level variables are used to control for racial diversity, population, and gender diversity. County-level and year indicators are included to control for county and year-fixed effects. To identify the effect of the law, I create a county-time varying indicator that takes a value of one for counties with an operational SSP after the state law is passed. Counties with an SSP after 2018 are the treated group; all other counties are the control. Table 1 presents the treatment and control population and crime means before and after law adoption. The treatment group includes the largest urban centers of Tennessee, increasing the magnitude of overdoses and population.

**Table 1 Descriptive Statistics**

| | **Pre-Treatment** | | **Post-Treatment** | |
|---|---|---|---|---|
| | **Treatment** | **Control** | **Treatment** | **Control** |
| Population | 507,986.90 | 44,808.45 | 514,828.30 | 45,964.03 |
| Fatal Overdose Rates | 30.33 | 23.577 | 38.33 | 30.17 |
| Nonfatal Overdose Rates | 328.38 | 383.40 | 346.22 | 358.93 |
| Gross Fatal Overdoses | 150.70 | 10.55 | 206.93 | 14.17 |
| Gross Nonfatal Overdoses | 1687.1 | 165.12 | 1901.40 | 165.69 |

*Notes: Overdose rates are overdoses per 100,000 individuals. Pre-treatment period is 2016-2017. Post-treatment period is 2018-2020. Treated group consists of counties with a legally operating SSP.*

## 1.4 Statistical Analysis

I use a DID approach to compare outcomes before and after the adoption of legalized SSPs in counties relative to counties that have not instituted an SSP. DID assumes that the pre-treatment trends in both the treatment group and the control are parallel. I estimate:

$$Y_{ct} = \beta_0 + \beta_1 SSP_{ct} + \beta_2 X_{ct} + \beta_3 County_c + \beta_4 Year_t + \varepsilon_{ct}.$$

Where $Y_{ct}$ is the outcome of interest for county *c* at time *t*. $SSP_{ct}$ is the interaction of a legally operating SSP located in county *c* at time *t* ,taking a value of 1 for treated counties from 2018-2020 and 0 for all other counties. $X_{ct}$ contains county-level covariates: population, percent white, percent black, percent male, and unemployment. $County_c$, and $Year_t$ are county and year fixed effects. For models estimated using only counties adopted in 2018, the two counties adopted after 2018 were excluded. The model is estimated using ordinary least squares. Standard errors are clustered at the county level and no weights were used.

Only five out of the ninety-five counties in Tennessee were in the treated group, which could potentially bias the standard errors. To address this, randomization inference was utilized. Randomization inference is an appropriate approach to estimating treatment effects with few treated cases (Conley and Taber 2011, Rosenbaum 2002). It considers what would have occurred under random assignments of treatment. It is conducted by randomly generating treatment statuses to obtain new p-values. The new p-value is the proportion of times the random treatment effect was larger than the estimated treatment effect. For this analysis, 2,500 permutations were done for randomization inference.

## 1.5 Results

Figures 1 and 2 present a graphical depiction of the trends for both fatal and nonfatal overdose rates. Visually, both figures appear visually similar and that is mathematically supported through the Wald test, shown in Table 2**.** The linear trends graph augments the DID model to include interactions of time with an indicator of treatment and plots the predictive values of this model for both treatment and control. First, I estimate the model with all counties in the model. The difference-in-differences result is presented in Table 3. All point estimates are positive in magnitude. Gross fatal overdoses are significant at the 10% level, showing an increase in the total number of overdoses in counties that implemented a SSP. The bottom of Table 3 is the model with only counties that adopted in 2018 included in the analysis. The two counties that adopted in 2019 were removed entirely from this model. Among these counties, fatal overdoses increased with the operation of an SSP. Again, all point estimates are positive; however, they are not statistically significant.

Next, I utilize random inference to account for the potential inference problems from too few treated counties. Column 1 of Table 4 presents the random inference p-values for fatal overdoses. The operation of an SSP increased fatal overdoses by roughly 37. The third column presents the results for nonfatal overdoses. The operation of an SSP increased nonfatal overdoses by approximately 175. Of note, both of these are gross number of overdoses. Columns 2 and 4 present the rate per 100,000 individuals, with both being positive but neither statistically significant. In 2020 COVID-19 created a shock around the world. This could have biased the results due to less drug use, less people carrying naloxone that could reverse an overdose, and a decreased ability to access the SSPs. For a robustness check I excluded 2020 from analysis to identify if the results hold. Excluding 2020 all point estimates in the non-randomized model are directionally the same, however none are significant. The randomization inference model results show an increase of 14.04 fatal overdoses and an increase of 121.87 nonfatal overdoses in treated counties, both of which are significant. These estimates are lower in magnitude than the model that included 2020, but directional the same and both are significant in each model.

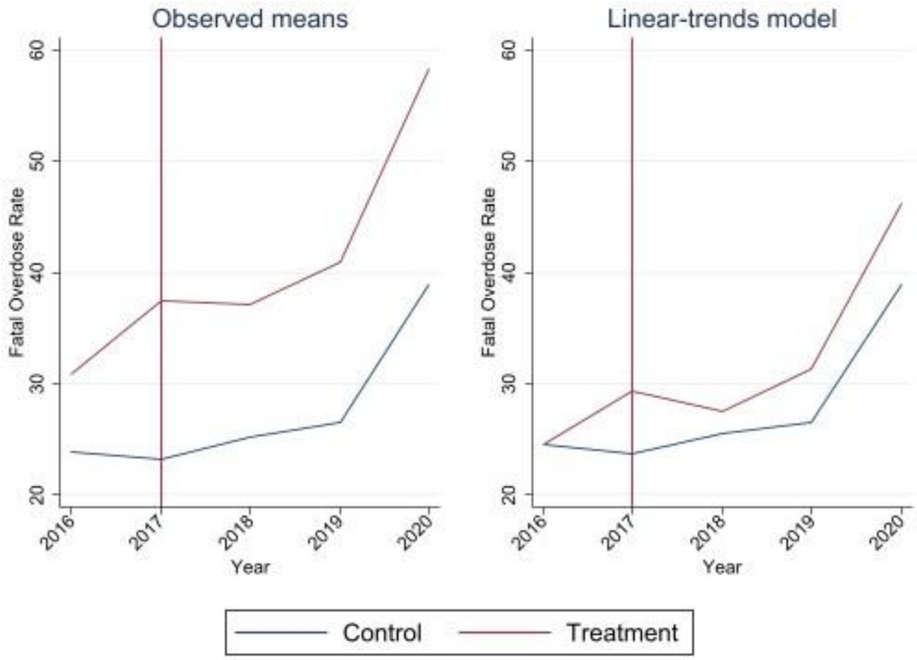


**Figure 1: Parallel Trends – Fatal Overdose Rates**

Notes: Overdose rates are per 100,000 individuals. Observed means graph is the mean fatal overdose rate for both treatment and control groups across the study. The linear trends graph augments the DID model to include interactions of time with an indicator of treatment and plots the predictive values of this model for both treatment and control.

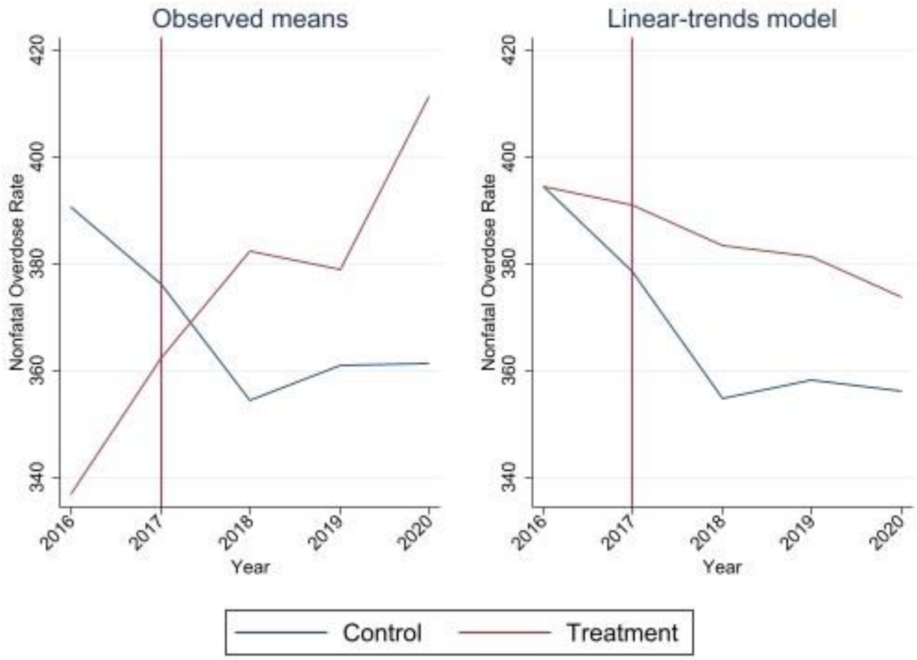


**Figure 2: Parallel Trends – Nonfatal Overdose Rates**

Notes: Overdose rates are per 100,000 individuals. Observed means graph is the mean fatal overdose rate for both treatment and control groups across the study. The linear trends graph augments the DID model to include interactions of time with an indicator of treatment and plots the predictive values of this model for both treatment and control.

**Table 2: Wald Test**

| Variable | P-Value |
|---|---|
| Fatal Overdose Rate | 0.256 |
| Nonfatal Overdose Rate | 0.691 |

*Notes: The Wald test identifies whether the linear trends in the outcome variable are parallel between the two groups in the pretreatment time period.*

# 1.6 Discussion

In this paper, I show the causal effects of operating an SSP on fatal and nonfatal overdoes in a county throughout Tennessee. Using random inference, I identify a positive and significant effect on gross fatal and nonfatal overdoses. Counties with an SSP had about 37 more fatal and 175 more nonfatal overdoses. These results are similar to a recent study looking at overdose mortality and SSPs throughout the United States (Packham 2022). However, that paper showed a significant result in overdose death rates, and my paper only shows a significant change in the gross number of overdoses. My findings suggest some effect on overdoses at the county level when an SSP is operational.

There are several limitations to this paper. SSPs are by no means a perfect proxy for naloxone distribution, as many organizations throughout the state provide this medication. Obtaining the number naloxone kits distributed in each county annually would be ideal in identifying the effect SSPs have on that. Secondly, in the time period of this study, all of the SSPs were located in urban environments where citizens have potentially greater access to illicit drugs which could decrease prices and increased usage. Once a greater number of SSPs begin operation in rural areas, an analysis comparing rural versus urban SSPs would be ideal to investigate if results are similar to other papers. Further, drug use is always changing in terms of drugs of abuse as well as unknown substances in the drug supply. Fentanyl has increased in popularity among drug manufacturers as a cutting agent, this extremely potent opioid has been attributed to the increase in overdose deaths throughout the country, and it is possible this substance is more common in urban areas, biasing the overdoses in the treated counties.

This paper investigates the very short run implications of legalizing SSPs. As more SSPs begin operation or become more well known the effects on overdoses may change. If there are moral hazard effects with naloxone saturation in a community, we will begin to see that. It is also possible that with an expansion of naloxone we see an increase in nonfatal overdoses, which would suggest that this expansion of distribution is effective at saving lives.

**Table 3: The Effects of SSPs on Overdose**

| All Counties | | |
|---|---|---|
| | Estimate | Clustered Standard Error |
| Fatal Overdoses | 60.07* | 35.18 |
| Nonfatal Overdoses | 189.83 | 146.21 |
| Fatal Overdoses per 100,000 | 2.12 | 3.46 |
| Nonfatal Overdoses per 100,000 | 11.09 | 30.65 |
| **2018 Counties** | | |
| | Estimate | Clustered Standard Error |
| Fatal Overdoses | 37.73** | 18.95 |
| Nonfatal Overdoses | 175.21 | 172.74 |
| Fatal Overdoses per 100,000 | 1.27 | 0.72 |
| Nonfatal Overdoses per 100,000 | 16.93 | 27.58 |

*Note: * p<0.10, ** p<0.05, *** p<0.01. Standard errors are clustered at the county level. Covariates include race, population, gender, and county and year fixed effects.*

**Table 4: Randomization Inference: 2018 Counties**

| | Fatal Overdoses | Fatal Overdoses per 100,000 | Nonfatal Overdoses | Nonfatal Overdoses per 100,000 |
|---|---|---|---|---|
| OLS Estimate | 37.73 | 1.27 | 175.21 | 16.93 |
| OLS p-value | 0.05** | 0.72 | 0.31 | 0.54 |
| Randomization Inference p-value | 0.00*** | 0.85 | 0.03* | 0.68 |

*Notes: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Standard errors are clustered at the county level. Covariates include race population, gender, and county and year fixed effects.*

**Table 5: The Effects of SSPs on Overdose – excluding 2020**

| | All Counties | |
|---|---|---|
| | Estimate | Clustered Standard Error |
| Fatal Overdoses | 24.03 | 17.01 |
| Nonfatal Overdoses | 98.17 | 88.71 |
| Fatal Overdoses per 100,000 | -0.71 | 2.64 |
| Nonfatal Overdoses per 100,000 | 2.67 | 24.82 |
| | **2018 Counties** | |
| | Estimate | Clustered Standard Error |
| Fatal Overdoses | 14.04 | 11.70 |
| Nonfatal Overdoses | 121.87 | 117.90 |
| Fatal Overdoses per 100,000 | -2.15 | 2.57 |
| Nonfatal Overdoses per 100,000 | 12.67 | 24.05 |

*Note: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Standard errors are clustered at the county level. Covariates include race population, gender, and county and year fixed effects.*

**Table 6: Randomization Inference - excluding 2020**

| | Fatal Overdoses | Fatal Overdoses per 100,000 | Nonfatal Overdoses | Nonfatal Overdoses per 100,000 |
|---|---|---|---|---|
| OLS Estimate | 14.04 | -2.15 | 121.87 | 12.67 |
| OLS p-value | 0.23 | 0.40 | 0.30 | 0.60 |
| Randomization Inference p-value | 0.00*** | 0.72 | 0.01*** | 0.77 |

*Notes: * p<0.10, ** p<0.05, *** p<0.01. Standard errors are clustered at the county level. Covariates include race population, gender, and county and year fixed effects.*

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# Chapter 2

# The Effects of Syringe Services Programs on Local Crime

## 2.1 Background

Not in my backyard (NIMBY) is a belief characterized by community resistance against social relief (Davidson and Howe 2015, Furr-Holden et al 2016). NIMBY is highly prevalent among services provided to people who use drugs including drug treatment facilities and syringe services programs (SSP) also known as needle exchanges (Smith 2011, Strike Myers and Millson 2004). Harm reduction services are at the forefront of the opioid epidemic. Designed to reduce adverse effects of drug use, harm reduction services intend to prevent overdose death, decrease the spread of infectious diseases, including HIV and HCV, and increase the overall well-being of individuals who use drugs until they are in a place to seek recovery efforts (Harm Reduction Coalition 2022). Despite the efficacy of SSPs in reducing HIV and HCV (Bushling et al 2021), arguments against SSPs are prevalent, including enabling drug use and an increase in crime in areas with these services (Davidson and Howe 2015, Rich and Adashi 2015).

Leveraging a change in the legal status of SSPs in Tennessee in 2018, I conduct a difference-in-differences (DID) analysis to identify the causal relationship between the introduction of an SSP in a given county and the rate of overall crime, crimes against people, crimes against property, and crimes against society. I use data from 2015 through 2020, three years pre-law change and three years' post-law change, including county demographics collected through the National Historical Geographic Information System (Manson et al. 2021), county crime numbers obtained through the Tennessee Bureau of Investigation (Tennessee Bureau of Investigation 2022), and number of sworn police officers reported to the Uniform Crime Reporting Program through the Federal Bureau of Investigation (Federal Bureau of Investigation 2022).

I provide new evidence on the causal relationship between the introduction of an SSP and the crime per capita in the area. In contrast to the opponents of SSPs, using DID, I find no statistically significant association between the introduction and operation of an SSP and the crime rate per capita at the county level. This is consistent with two previous studies conducted in Baltimore, Maryland and New York City (Galea et al. 2001, Marx et al. 2000). The current study expands upon the research previously conducted by using a quasi-experimental design, as opposed to a cross-sectional survey conducted in New York City or Poisson regression conducted in Baltimore, to isolate the causal effects of SSPs and crime.

Showing a lack of evidence to suggest an increase in crime has significant public health implications. First, communities should be able to feel more confident that offering this social service will not decrease the safety of the community. Second, policymakers will be able to confidently make policies to protect individuals who inject drugs from acquiring HIV or HCV through the use of SSPs without putting communities at increased risk of crime.

In the next section, I will discuss previous literature surrounding SSPs and crime, looking at results and areas of improvement for these studies. Section II will discuss the data that I use, where it was obtained, and the generalizability of it. Section III will show the models I use, their assumptions, and their reliability in identifying causal effects. Section IV will show the results of the difference-in-difference and randomization analysis. Lastly, section V will conclude this paper with a discussion of the limitations and future research needs surrounding harm reduction services.

## 2.2 Previous Literature

Two previous studies have looked at the causal effects of SSPs and crime. Marx et al. (2000) utilized arrest records before and after the introduction of an SSP in Baltimore. Looking at specific types of crime, including drug possession, economically motivated crime, resisting police, and violence, the authors used a Poisson regression to identify changes in mean arrests pre- and post-SSP introduction. No statistically significant differences were found in the mean number of arrests for any of the specific crimes the authors investigated.

A second study conducted in New York City used a cross-section survey of residents in Harlem reporting violence they were aware of or had personally experienced. The respondents were then geocoded to obtain the distance to the nearest SSP. Logistic regression was utilized to assess the relationship between violence and distance to the nearest SSP. Galea et al. (2001) found no consistent association between living close to an SSP and reported violence.

While both of these studies suggest that SSPs are not associated with an increase in crime, both have flaws that make it vital to conduct a more rigorous approach. The New York City study leverages a cross-sectional survey of reported violence. These data are unreliable in assessing actual crime, only what the population heard about, not what was reported to or by the police of the area. The Baltimore study provides better evidence using police arrest data. However, since the study relies on data from one urban environment, further research is needed to see if this is consistent across more locations. Also, a more rigorous methodological approach is needed to isolate the causal effects of introducing an SSP and the crime in a given area.

## 2.3 Data

Beginning in 2018, Tennessee legalized the operation of syringe services programs. In order to begin the operation of an SSP, organizations must apply for authorization through the Tennessee Department of Health. As of 2020, the most recent year crime rates are available, five counties had an operational SSP. Davidson, Hamilton, Knox, and Washington began operating in 2018, while Shelby began in 2019. The data for this study comes from multiple sources. County-level crime numbers were extracted from the Tennessee Bureau of Investigation's online crime portal. All state, county, and municipal law enforcement and correctional agencies submit data to the Tennessee Bureau of Investigation (Tennessee Bureau of Investigation 2003). This publicly available data is what is provided to the Federal Bureau of Investigation for the National Incident Based Reporting System (NIBRS). It provides the aggregate number of offenses, crimes, and incidents in each county throughout Tennessee for a given year. One limitation of aggregate county level crime is that the effect of SSPs on crime may be at a more detailed level (zip code or census tract) and it is not on the county level affecting crime, but at the local level it is. However, with as few SSPs as there are throughout Tennessee during the study period, residents of surrounding areas are required to travel into these counties that have organizations providing these services. For example, SSPs in Memphis serve clients from Arkansas, Mississippi, Nashville serves clients from Cheatham, Dickson and the other surrounding counties, while Knoxville serves clients as far away as Johnson City. Individuals traveling to the counties with SSPs, if they are more inclined to commit a crime, would potentially increase crime at the county level. County demographic information was extracted from IPUMS National Historical Geographic Information System. (NHGIS). NHGIS provides free online access to summary statistics and GIS files for the U.S. censuses and other nationwide surveys from 1790 through the present. Population data are collected through the decennial censuses and the American Community Survey (Manson et al. 2021). Through a partnership with the Tennessee Department of Health I was able to obtain the years each legally operating SSP was licensed. Unemployment data was acquired from the State of Tennessee Department of Labor and Workforce Development (T.N. Department of Labor and Workforce Development 2022).

I use data from all 95 counties in Tennessee, including demographics, police presence, overall crime rates, crimes against people, crimes against property, and crimes against society, as well as if the county had a legal SSP in a given year. Crimes against persons include robbery, rape, murder, assault. These are crimes in which the victim is always the individual. Crimes against property include burglary, theft, arson, and vandalism. These are crimes that involve the taking of property or money with no threat of force against the victim. Crimes against society include gambling, prostitution, and drug offenses. These are crimes that involve the public prohibition against engaging in certain behaviors and are typically victimless crimes. A list of all crimes associated with each category is provided in Appendix A. Counties were treated as having an SSP if an organization within the county applied for and was granted licensure to operate within a given year. Five of the ninety-five counties were treated at some point in the study time period.

The outcome of interest is the county-level crime rate. Crime rate is measured as number of crimes per 100,000 individuals. County-level variables control a specific county's racial diversity, total population and gender diversity. I create a set of county-level indicators to account for differences across counties. To identify the effect of the law, I create a county-time varying indicator that takes a value of one for counties with an operational SSP after the state law is passed. Counties with an SSP after 2018 are the treated group; all other counties are the control. Table 1 shows the mean populations and crime of both the control and the treatment groups for each year. The treatment group includes the largest urban centers of Tennessee, increasing the magnitudes of crime and the population.

**Table 1: Summary Statistics**

| | Pre-Treatment | | Post-Treatment | |
|---|---|---|---|---|
| | Treatment Counties | Control Counties | Treatment Counties | Control Counties |
| Population | 506,260.70 | 44,633.68 | 514,828.30 | 45,964.03 |
| Total Crime per 100k | 10,087.07 | 5,995.52 | 9,666.84 | 5,353.57 |
| Crime against Persons per 100k | 2,674.99 | 1,545.10 | 2,604.13 | 1,392.54 |
| Crime against Property per 100k | 5,741.60 | 3,182.10 | 5,513.72 | 2,586.71 |
| Crime against society per 100k | 1,670.48 | 1,268.32 | 1,549.00 | 1,374.31 |
| Total Crime- Gross | 57,600.80 | 2,989.25 | 56,000.00 | 2,822.53 |
| Crime against Persons- Gross | 16,609.13 | 791.53 | 16,241.93 | 744.23 |
| Crime against Property- Gross | 32,142.40 | 1,596.74 | 31,717.33 | 1,373.40 |
| Crime against society- Gross | 8,849.27 | 600.98 | 8,040.733 | 704.90 |

*Notes: Pre-treatment is time period 2015-2017. Post-treatment is 2018-2020. Treated counites consist of those with a legally operational*

## 2.4 Statistical Analysis

I use a difference-in-differences approach to compare outcomes before and after the adoption of legalized SSPs in counties relative to counties that have not instituted an SSP. Difference-in-differences assumes that the policy was not adopted in response to the outcome, which in this case holds. Legalizing SSPs is an effort to reduce the spread of infectious diseases among injection drug users, not to affect the crime in a given area. Further, DID assumes that the pre-treatment trends in both the treatment group and the control are parallel. I estimate:

$$Y_{ct} = \beta_0 + \beta_1 SSP_{ct} + \beta_2 X_{ct} + \beta_3 County_c + \beta_4 Year_t + \varepsilon_{ct}.$$

Where $Y_{ct}$ is the outcome of interest for county *c* at time *t*. $SSP_{ct}$ is the policy measure taking a value of 1 if an SSP was operational in county *c* at time *t*. $X_{ct}$ contains the county-level covariates, population, percent white, percent black, percent male, and police per capita, and unemployment. $County_c$, and $Year_t$ are the county and year fixed effects. Next, I look at early adopting counties, defined as counites that had a legally operating SSP in the first year. These counties were Davidson, Hamilton, and Knox. Lastly, because COVID-19 affected all aspects of life the model is again estimated with 2020 removed from analysis. The model is estimated using ordinary least squares. Standard errors are clustered at the county level.

Only five out of the ninety-five counties in Tennessee were in the treated group, which could potentially bias the standard errors. To address this, randomization inference was utilized. Randomization inference is an appropriate approach to estimating treatment effects with few treated cases (Conley and Taber 2011, Rosenbaum 2002). It considers what would have occurred under random assignments of treatment. It is conducted by generating random treatment statuses and re-estimating the original regression to obtain a new p-value. The new p-value is the proportion of times the random treatment effect was larger than the estimated treatment effect. For this analysis 2,500 permutations were done for randomization inference.

## 2.5 Results

Figures 1 through 8 are graphical depictions of the parallel trends for each outcome variable. Trends visually look parallel. Table 2 presents the mathematical determination of parallel trends. The only variable that is not parallel is gross crime against society. These results are still presented and discussed further in the discussion. Based on the results of the linear trends models, the parallel trends assumption is satisfied. All of the SSPs that began operation in this study are in urban areas. This potentially can introduce bias to the study. Figures 9-12 are graphical trends of total crime per capita, crime against persons, crime against property, and crime against society by population density. Total crime trends visually appear to be similar regardless of population density, increasing at first before decreasing in 2020. Crime against persons is similar in the lowest three quartiles, decreasing across all years. However, in the highest quartile crime against persons increases before decreasing. Crime against property and crime against society are trending similarly across all population densities.

Table 3 presents the results from the difference-in-differences model. The first column presents the crime per 100,000 for all counties in Tennessee. While the results of this model are not statistically significant, it is noteworthy that the direction of total crime is positive. Further research needs to be conducted to see if these results are similar in other states or countries.

The second column presents the gross crime numbers for all counties. Column 3 presents the crime per 100,000 for all counties adopting an SSP in 2018. For the three counties that adopted in 2018, Davidson, Hamilton, and Knox, crime per capita is decreasing, although not significantly different from zero, and the decrease is entirely impacted by a decrease in crime against society. Of note, crime against society in counties that implemented an SSP decreased by about 190 crimes per capita. This potentially suggests that drug-related crime decreased due to the legalization of SSPs. Column 4 presents the gross crime numbers for counties adopting an SSP in 2018. Magnitudes of crime per 100,000 were mainly positive with the exception of crime against society, and this occurred both with all counties and omitting counties adopting after 2018. Also, of note gross crime is decreasing in both models and across all categories of crime. This is potentially impactful because total number of crimes decreased after the legislation.

In March 2020, COVID-19 shook the world with lockdowns and restrictions for the general population. I remove 2020 from the model to account for this to investigate whether the results hold or not. After the removal of 2020, magnitudes decreased in every model. However, the estimates' directions stayed the same. Crime against society is still negative in every model, and gross crime is decreasing across all categories of crime. This suggests that COVID-19 had an impact on the number of crimes committed, but the results are still similar.

I continue the analysis using randomization inference. Randomization inference could only be used for counties adopting in 2018, so two counties were excluded from the analysis. Column 1 of Table 3 shows total crime per 100,000. Column 2 presents total gross crime numbers. Columns 3 and 4 present crime against property per 100,000 and gross, respectively. Columns 5 and 6 show crimes against persons per 100,00 and gross, respectively. Columns 7 and 8 show crimes against society per 100,000 and gross, respectively. Utilizing randomization inference resulted in two results showing significant decreases in both total gross crime and gross crime against society. These decreases suggest that the legislation is implemented with fidelity. Legalizing SSPs includes allowing people who use substances to possess syringes, which previously would have been considered paraphernalia. Showing a significant decrease in crime against society would account for this.

Randomization inference to remove 2020 because of COVID-19 showed interesting results. Similar to the previous model's gross crime and gross crime against society were both significant and negative. However, all categories of crime per capita showed changes. Both crime against property and crime against persons increased per capita while crime against society per capita decreased. This potentially suggests that the legalization of SSPs increases certain types of crime, which may outweigh the benefits provided by SSPs.

## 2.6 Discussion

In this paper, I isolate the causal effects of opening and operating a syringe services program on crime in Tennessee. I find no significant results for the presence of an SSP on crime rate. This is similar to previous Baltimore and New York City studies that found no association with SSPs and crime rates. Further, this study is a larger sample with a more rigorous model than either of the aforementioned studies, leading to increased generalizability. When utilizing randomization inference, both gross crime and gross crime against society significantly decrease in counties with an SSP. When removing 2020 due to COVID-19 crime against property and crime against persons per capita increased while crime against society per capita decreased. This suggests that the legalization of SSPs may increase certain types of crime. The possibility of this needs to be weighed against the decrease in the spread of infectious diseases attributed to SSPs.

The SSP legislation in Tennessee is still fairly new. This paper identifies the short run implications of legally operating SSPs on crime but much could change over the long run. Law enforcement is still learning how to enforce the regulation and SSPs are still relatively unknown to a large portion of the community; as these evolve changes in crime rates may be affected in the communities. Further, as more counites begin to have an operating SSP we will be able to identify if there was spillover effects from surrounding areas due to individuals needing to travel to a different county to utilize the services.

There are several limitations with this study. First, all counties that adopted an SSP are urban areas. It would be beneficial for there to be a rural county that operates an SSP. Second, the locations and hours of SSPs are not hidden and potentially could lead to a greater police presence in the locations that the operate, leading to increases in arrests. Third, one outcome variable did not pass the parallel trends assumption, potentially biasing these results. While they show no significant result, this could be because of this violation.

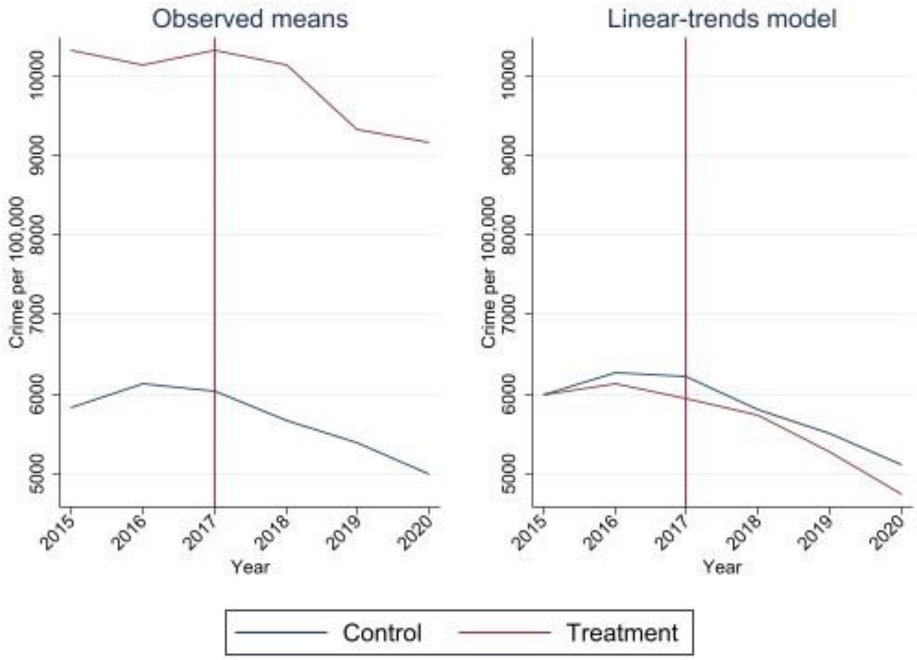


**Figure 1: Parallel Trends – All Crime per Capita**

*Notes: Observed means graph is the mean fatal overdose rate for both treatment and control groups across the study. The linear trends graph augments the DID model to include interactions of time with an indicator of treatment and plots the predictive values of this model for both treatment and control.*

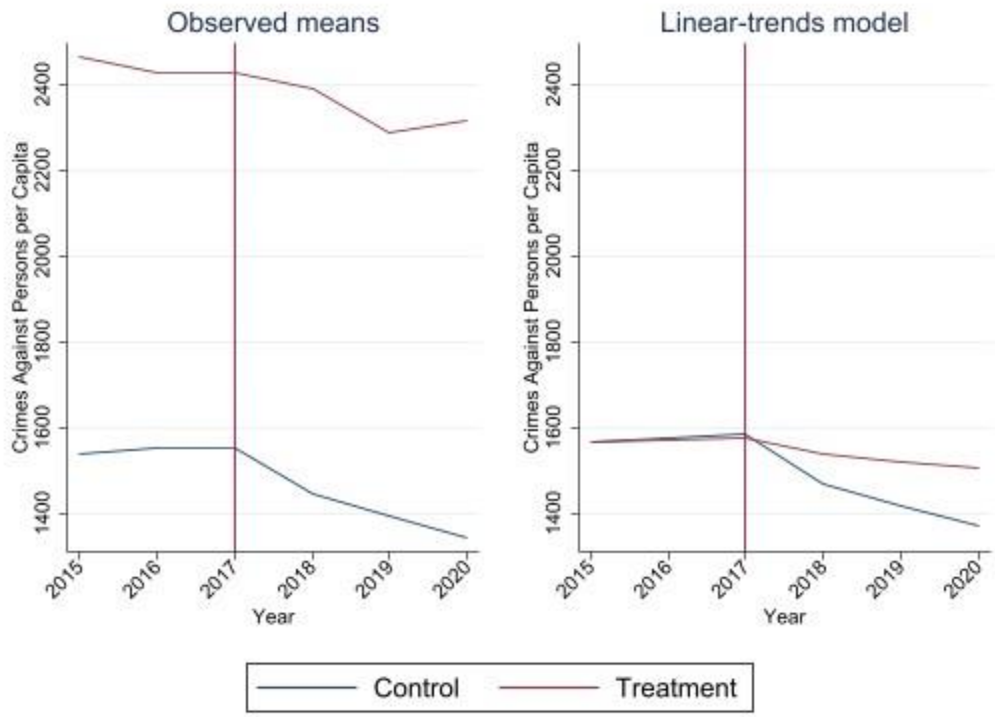


**Figure 2: Parallel Trends – Crime Against Persons per Capita**

*Notes: Crime per capita is crime per 100,000. Observed means graph is the mean fatal overdose rate for both treatment and control groups across the study. The linear trends graph augments the DID model to include interactions of time with an indicator of treatment and plots the predictive values of this model for both treatment and control.*

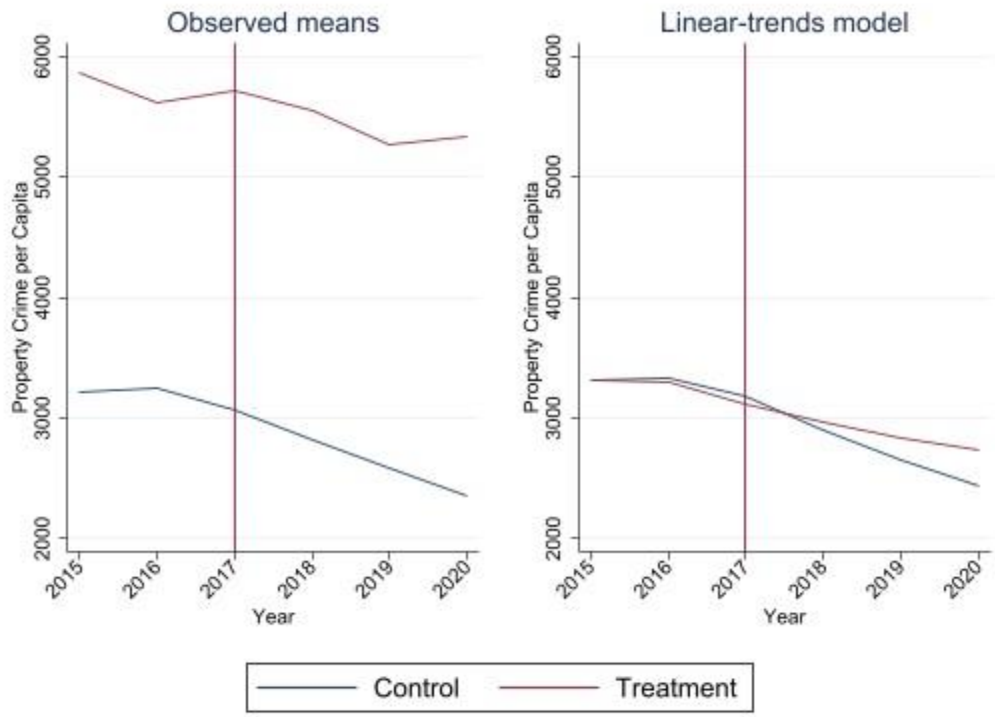


**Figure 3: Parallel Trends – Crime Against Property per Capita**

*Notes: Crime per capita is crime per 100,000. Observed means graph is the mean fatal overdose rate for both treatment and control groups across the study. The linear trends graph augments the DID model to include interactions of time with an indicator of treatment and plots the predictive values of this model for both treatment and control.*

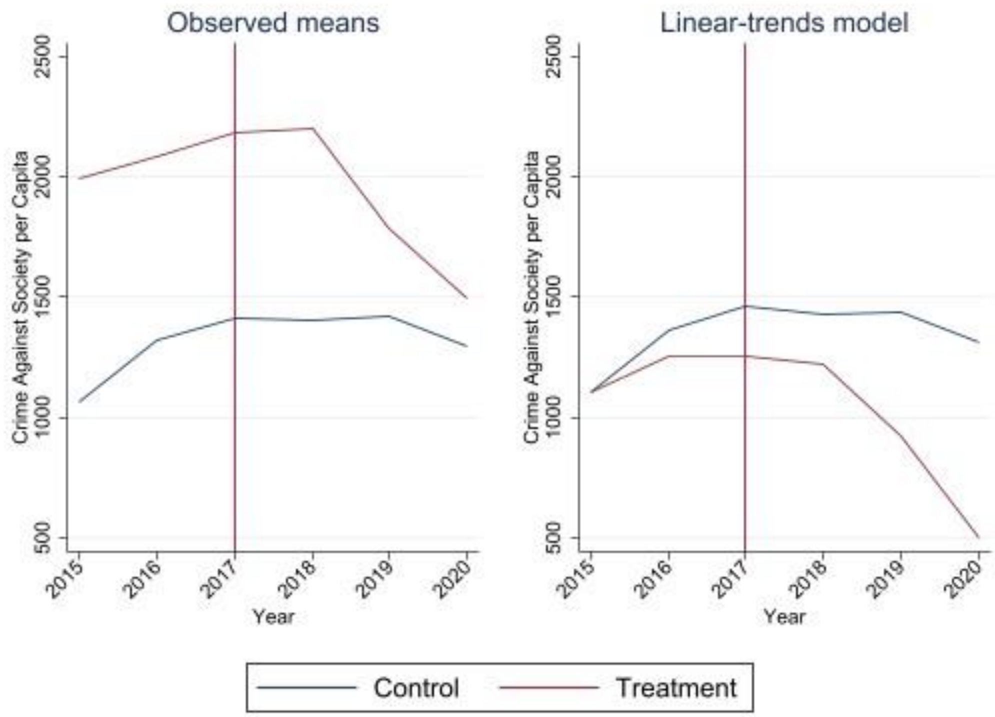


**Figure 4: Parallel Trends – Crime Against Society per Capita**

*Notes: Crime per capita is crime per 100,000. Observed means graph is the mean fatal overdose rate for both treatment and control groups across the study. The linear trends graph augments the DID model to include interactions of time with an indicator of treatment and plots the predictive values of this model for both treatment and control.*

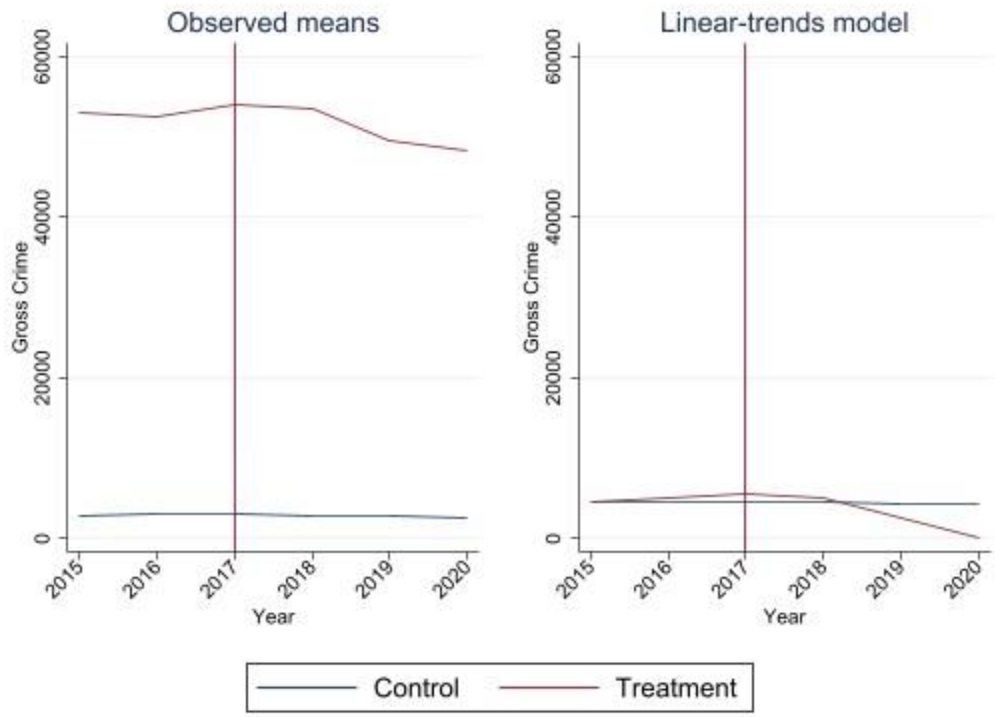


**Figure 5: Parallel Trends – Gross All Crime**

*Notes: Observed means graph is the mean fatal overdose rate for both treatment and control groups across the study. The linear trends graph augments the DID model to include interactions of time with an indicator of treatment and plots the predictive values of this model for both treatment and control.*

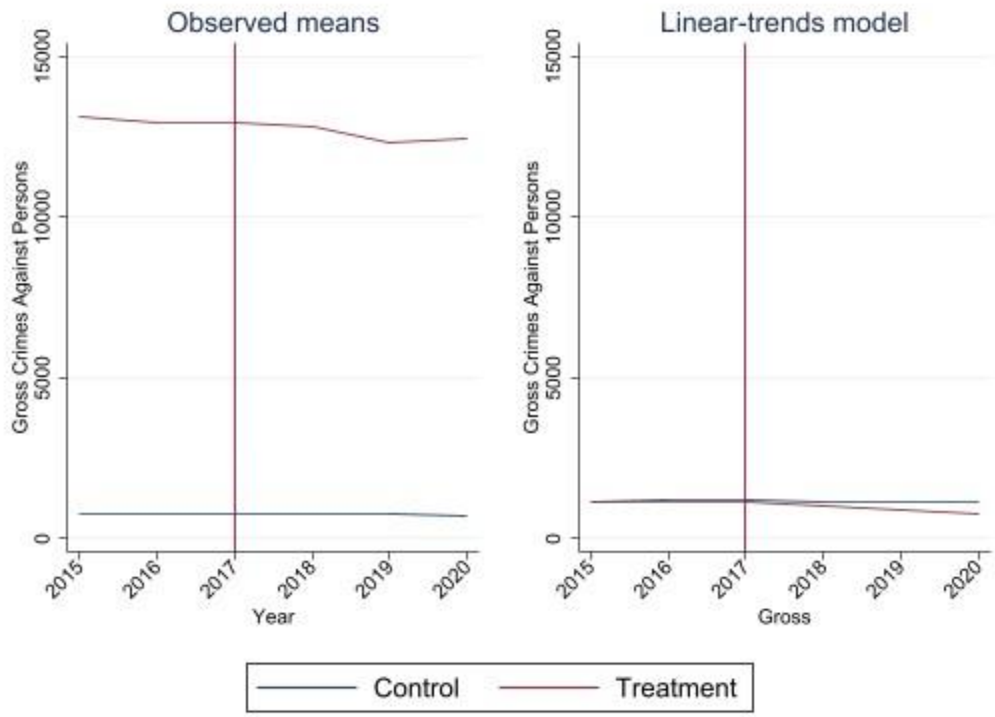


**Figure 6: Parallel Trends – Gross Crime Against Persons**

*Notes: Observed means graph is the mean fatal overdose rate for both treatment and control groups across the study. The linear trends graph augments the DID model to include interactions of time with an indicator of treatment and plots the predictive values of this model for both treatment and control.*

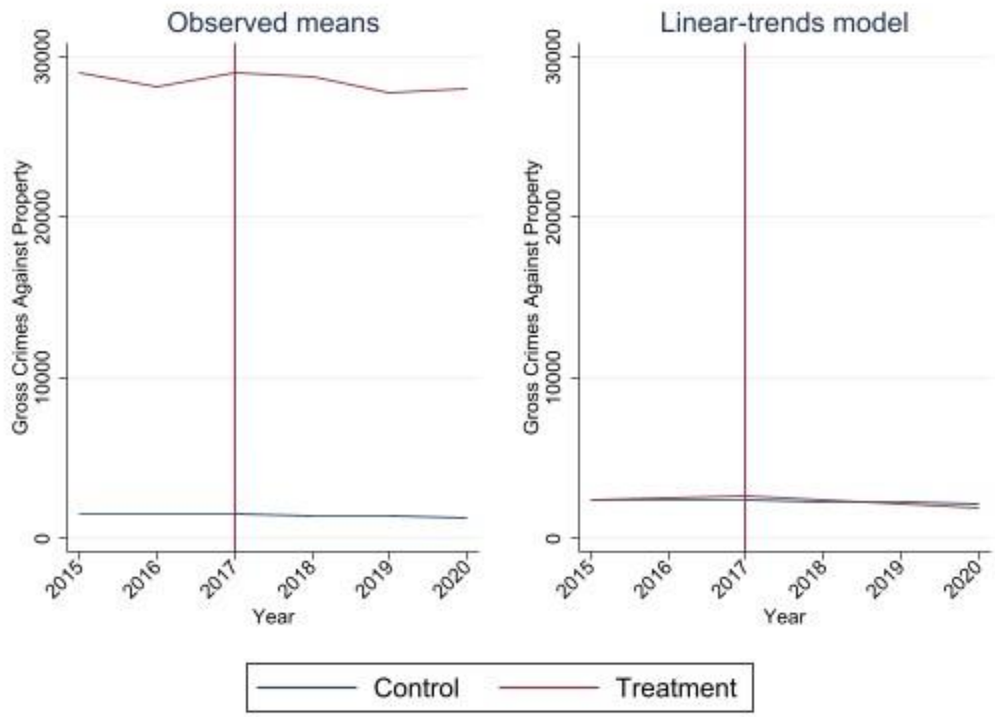


**Figure 7: Parallel Trends – Gross Crime Against Property**

*Notes: Observed means graph is the mean fatal overdose rate for both treatment and control groups across the study. The linear trends graph augments the DID model to include interactions of time with an indicator of treatment and plots the predictive values of this model for both treatment and control.*

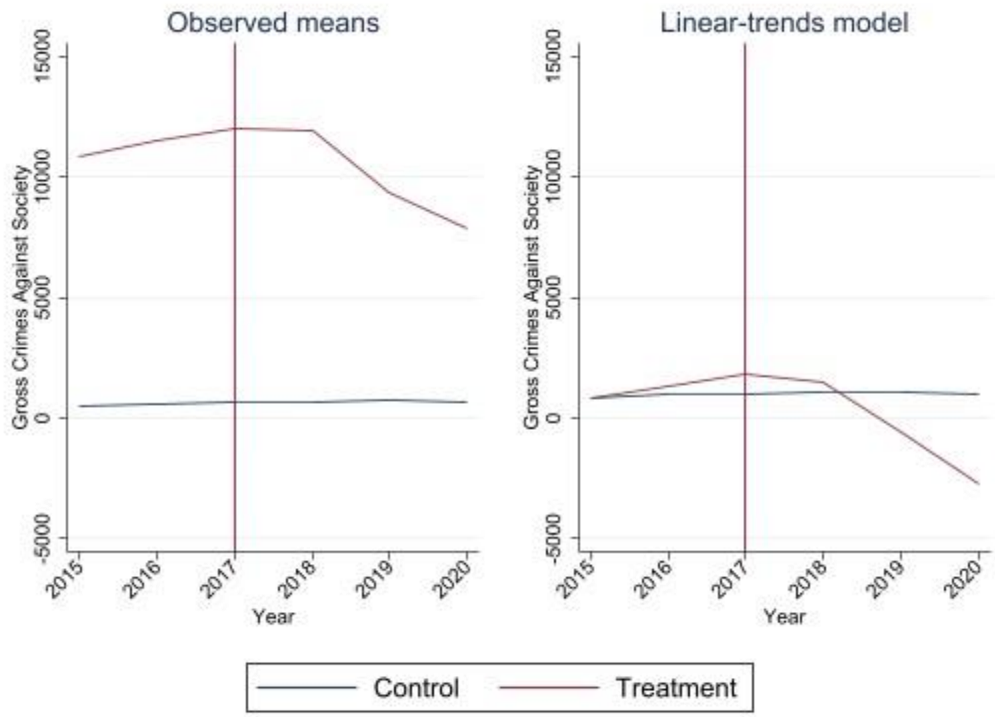


**Figure 8: Parallel Trends – Gross Crime Against Society**

*Notes: Observed means graph is the mean fatal overdose rate for both treatment and control groups across the study. The linear trends graph augments the DID model to include interactions of time with an indicator of treatment and plots the predictive values of this model for both treatment and control.*

**Table 2: Wald Test**

| **Variable** | **F** | **P-value** |
|---|---|---|
| All Crime per 100,000 | 0.74 | .39 |
| Crime against Persons per 100,000 | 0.01 | .94 |
| Crime against property per 100,000 | 0.09 | .76 |
| Crime against society per 100,000 | 4.92 | .03* |
| All crime gross | 0.57 | .45 |
| Crime against persons gross | 0.01 | .92 |
| Crime against property gross | .03 | .87 |
| Crime against society gross | 13.72 | .000** |

*Notes: The Wald test identifies whether the linear trends in the outcome variable are parallel between the two groups in the pretreatment time period.*

**Table 3: Effects of SSPs on Crime**

| Total crime | Crime against persons | Crime against property | Crime against society |
|---|---|---|---|
| *Panel A: All counties - crime per 100,000* | | | |
| 193.03 | 100.61 | 282.63 | -190.22 |
| (260.82) | (75.70) | (197.22) | (194.13) |
| *Panel B: All counties gross crime* | | | |
| -1839.46 | -287.34 | -676.97 | -875.15 |
| (1162.87) | (374.35) | (1141.59) | (1175.20) |
| *Panel C: Only counties adopting in 2018- crime per 100,000* | | | |
| -51.35 | 104.92 | 198.11 | -354.38 |
| (401.46) | (126.53) | (316.37) | (317.89) |
| *Panel D: Only counties adopting in 2018- gross crime* | | | |
| -2247.27 | -215.68 | -161.93 | -1869.66 |
| (1842.81) | (588.30) | (1717.70) | (1942.54) |

*Note: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Standard errors are clustered at the county level. Covariates include controls for race, gender, population, sworn police officers per capita, county, year.*

**Table 4: Randomization Inference - Effects of SSPs on Crime**

| | Gross Crime | | | |
|---|---|---|---|---|
| | All Crime Gross | Gross crime against property | Gross crime against persons | Gross crime against society |
| OLS Estimate | -2247.27 | -161.93 | -215.68 | -1869.66 |
| OLS p-value | 0.23 | 0.93 | 0.72 | 0.34 |
| Randomization Inference p-value | 0.00*** | 0.21 | 0.07* | 0.03** |
| | Crime per Capita | | | |
| | All Crime per 100k | Crime against property per 100k | Crime against persons per 100k | Crime against society per 100k |
| OLS Estimate | -51.35 | 198.11 | 104.92 | -354.38 |
| OLS p-value | 0.90 | 0.53 | 0.41 | 0.27 |
| Randomization Inference p-value | 0.91 | 0.40 | 0.43 | 0.13 |

**Table 5: Effects of SSPs on Crime – Pre COVID-19 (2015-2019)**

| Total crime | Crime against persons | Crime against property | Crime against society |
|---|---|---|---|
| *Panel A: All counties - crime per 100,000* | | | |
| 126.11 | 94.40 | 176.23 | -144.52 |
| (231.52) | (72.12) | (205.48) | (169.62) |
| *Panel B: All counties gross crime* | | | |
| -1319.91 | -260.51 | -390.95 | -668.45 |
| (900.71) | (358.13) | (1048.30) | (959.00) |
| *Panel C: Only counties adopting in 2018- crime per 100,000* | | | |
| -68.56 | 95.43 | 55.41 | -219.39 |
| (323.25) | (102.46) | (287.07) | (258.86) |
| *Panel D: Only counties adopting in 2018- gross crime* | | | |
| -1667.50 | -144.62 | -443.32 | -1079.56 |
| (1333.26) | (455.73) | (1603.35) | (1498.90) |

*Note: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Standard errors are clustered at the county level. Covariates include controls for race, gender, population, sworn police officers per capita, county, year.*

**Table 6: Randomization Inference: Effects of SSPs on Crime Pre-COVID (2015-2019)**

| | Gross Crime | | | |
|---|---|---|---|---|
| | All Crime Gross | Gross crime against property | Gross crime against persons | Gross crime against society |
| OLS Estimate (95% Confidence Interval) | -1667.50 (-4315.47-980.47) | -443.32 (-3627.72-2741.07) | -144.62 (1049.74-760.50) | -1079.56 (-4056.49-1897.38) |
| OLS p-value | .214 | .783 | .752 | .473 |
| Randomization Inference p-value | .000** | .059 | .122 | .034* |
| | Crime per Capita | | | |
| | All Crime per 100k | Crime against property per 100k | Crime against persons per 100k | Crime against society per 100k |
| OLS Estimate (95% Confidence Interval) | -68.56 (-710.56-573.45) | 55.41 (-514.62-625.43) | 95.43 (-108.06-298.92) | -219.39 (-733.51-294.74) |
| OLS p-value | .833 | .847 | .354 | .399 |
| Randomization Inference p-value | .867 | .797 | .460 | .328 |

*Note: * p<0.10, ** p<0.05, *** p<0.01. Standard errors are clustered at the county level. Covariates include controls for race, gender, population, sworn police officers per capita, county, year.*

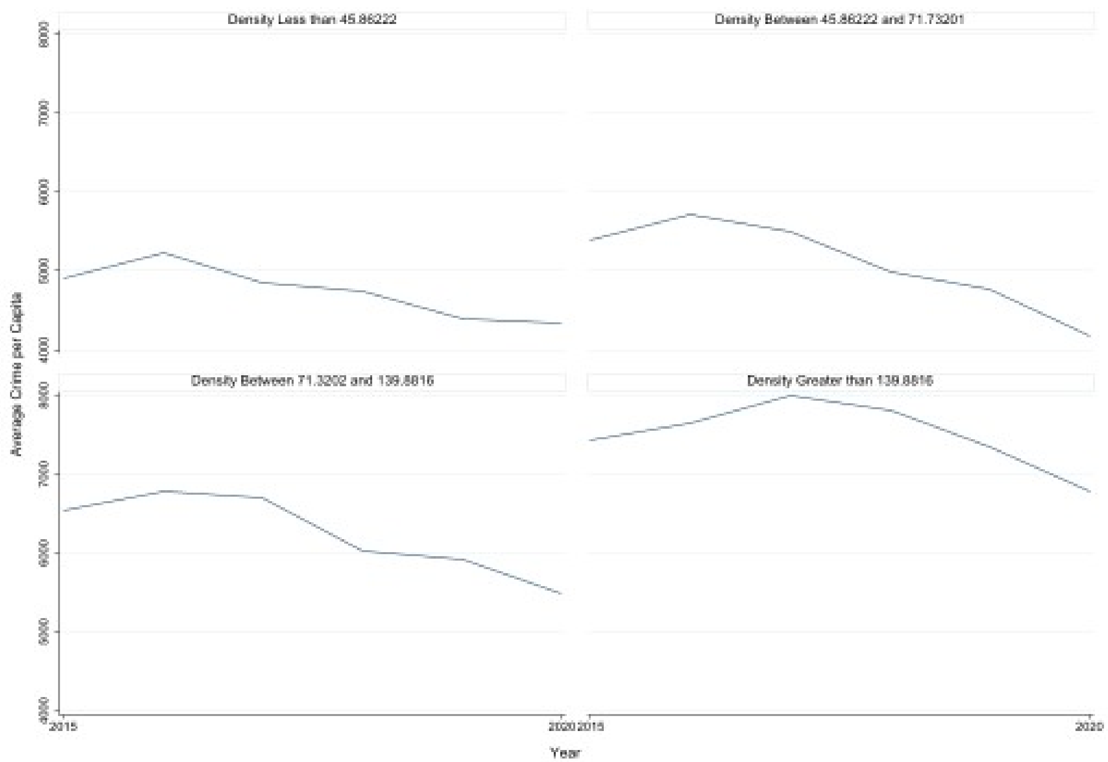


**Figure 9: Average Total Crime by Population Density**

*Notes: Counties are grouped into quartiles of population density. Source: US Census Bureau*

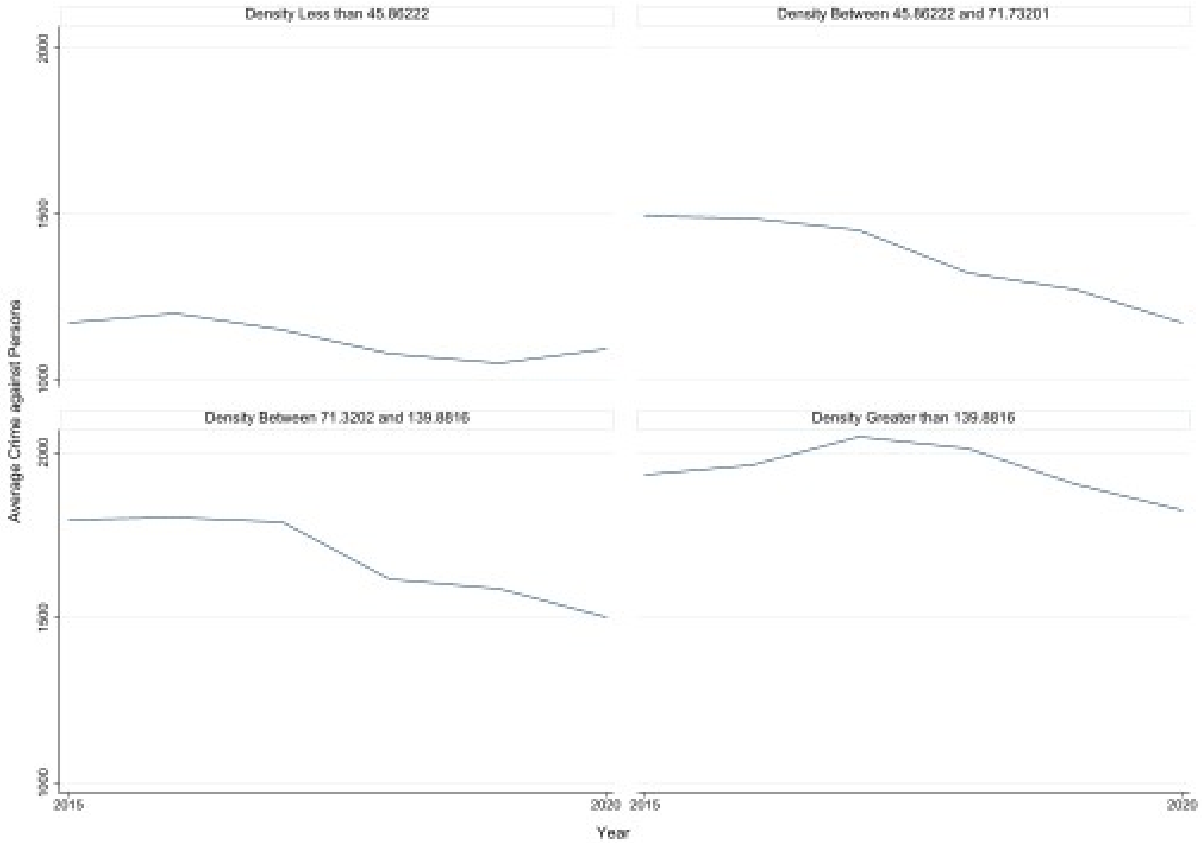


**Figure 10: Average Crime Against Persons by Population Density**

*Notes: Counties are grouped into quartiles of population density. Source: US Census Bureau*

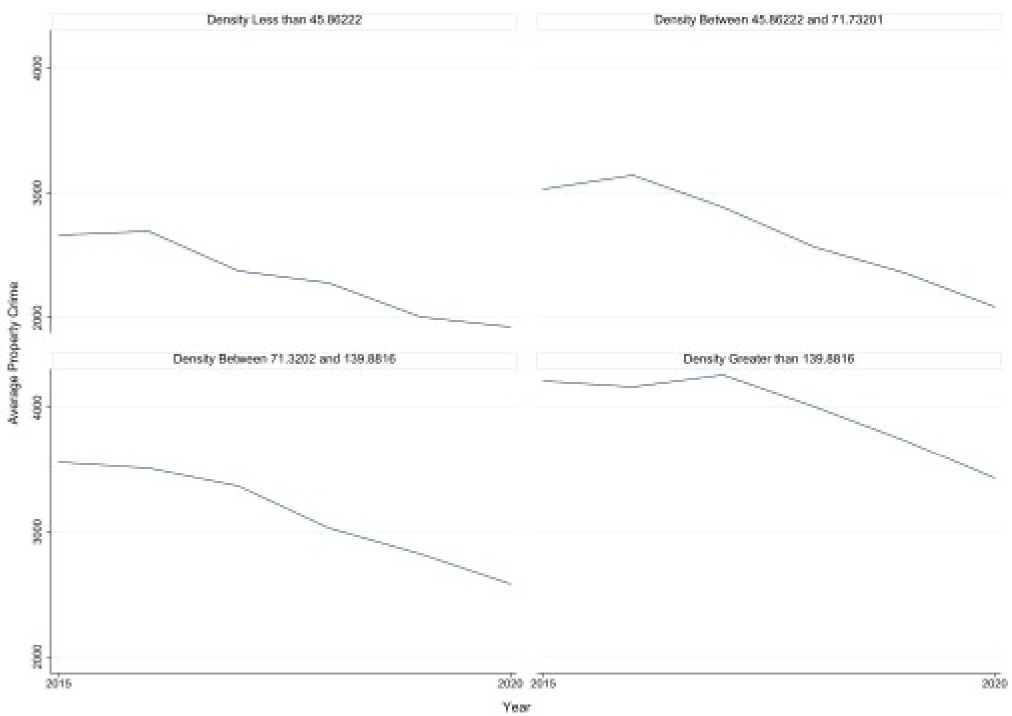


**Figure 11: Average Crime Against Property by Population Density**

*Notes: Counties are grouped into quartiles of population density. Source: US Census Bureau*

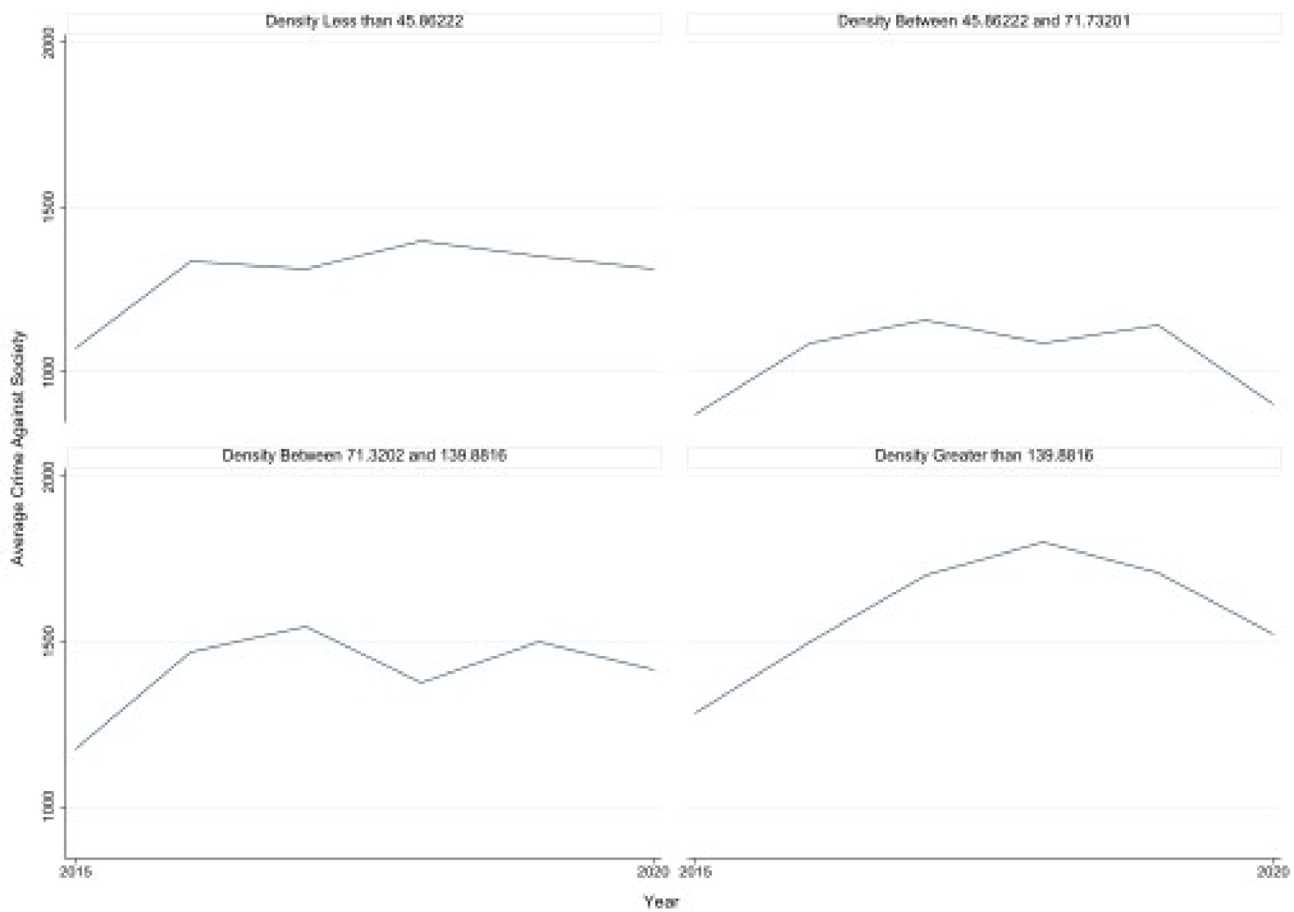


**Figure 12: Average Crime Against Society by Population Density**

*Notes: Counties are grouped into quartiles of population density. Source: US Census Bureau*

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| Appendix A: Types of Crime | | |
|---|---|---|
| **Crimes Against Persons** | **Crimes Against Property** | **Crimes Against Society** |
| Murder | Arson | Animal Cruelty |
| Negligent Manslaughter | Bribery | Drug/Narcotics Violations |
| Negligent Vehicular Manslaughter | Burglary | Drug/Narcotics Equipment Violations |
| Kidnapping/Abduction | Counterfeiting/Forgery | Gambling – Betting/Wagering |
| Forcible Rape | Destruction/Damage/Vandalism | Gambling – Operating/Promoting |
| Forcible Sodomy | Embezzlement | Gambling – Equipment Violations |
| Sexual Assault W/ Object | Extortion/Blackmail | Gambling – Sports Tampering |
| Forcible Fondling | Fraud-False Pretenses | Pornography/Obscene Material |
| Incest | Fraud – Credit Card/ATM | Prostitution |
| Statutory Rape | Fraud – Impersonation | Prostitution Assisting/ Promoting |
| Aggravated Assault | Fraud- Welfare | Purchasing Prostitution |
| Simple Assault | Fraud – Wire | Weapon Laws Violations |
| Intimidation | Fraud – Identity Theft | |
| Stalking | Fraud- Computer Hacking/Invasion | |
| Commercial Sex Acts | Robbery | |
| Involuntary Servitude | Theft- Pick Pocketing | |
| | Theft- Purse Snatching | |
| | Theft – Shoplifting | |
| | Theft from Building | |
| | Theft from Coin Machine | |
| | Theft from Motor Vehicle | |
| | Theft of Motor Vehicle Parts | |
| | Theft – All other Larceny | |
| | Motor Vehicle Theft | |
| | Stolen Property | |

# Chapter 3
# Effects of Supply-Side Interventions on Drug Use and Drug Overdose: The Results from Sodium Permanganate Regulation

## 3.1 Background

Drug overdose deaths have increased dramatically since 1999, with over one million individuals experiencing a fatal overdose (CDC 2023). Between 1999 and 2006, cocaine-related overdose deaths increased from 1.26 to 2.50 per 100,000 (McCall Jones et al., 2017). The United States government has attempted multiple times to regulate essential chemicals used in the production of cocaine with varying degrees of success. In 2006, sodium permanganate was classified as a List II chemical, establishing thresholds for domestic and international transactions (Cunningham et al., 2016). This regulation has been shown to have decreased cocaine seizures, increased price, and decreased purity (Cunningham et al., 2015). The present study investigates the effects of this regulation on the number of people who use cocaine, its effects on the number of deaths related to cocaine, and its effects on substitute illicit drug use, specifically methamphetamine.

Nearly all cocaine is produced in Columbia, Peru, and  Bolivia, as coca plants are native to South America. Historically, coca leaves were used medicinally; however, it was quickly realized that it was highly addictive. Today, cocaine is classified as a Schedule II drug under the Controlled Substances Act, meaning it is highly addictive and has an accepted medical use (DEA 2020). In cocaine production, coca leaves are harvested and then chemically altered to produce coca paste. Oxidizing agents such as potassium permanganate or sodium permanganate are then used to convert the paste to cocaine base, which is then adulterated further to create a powder commonly sold worldwide. Potassium permanganate was regulated heavily in 1989 by the United States. This regulation resulted in a decrease in the availability throughout the 1990s, however, in the 2000s, the world's largest producer of potassium permanganate greatly increased its production of sodium permanganate (Cunningham et al., 2015, 2016). Both substances are interchangeable and integral in cocaine manufacturing, and the regulations of both have been shown to have decreased the availability of cocaine in the United States.

Little research has been conducted on the impacts of sodium permanganate regulation on cocaine users, cocaine-related overdoses, and substitution to other illicit drugs. Two studies utilized autoregressive integrated moving average (ARIMA) to investigate the regulation on U.S. cocaine seizures, cocaine purity, cocaine price, past year and past month use (Cunningham et al., 2015, 2016). Past year cocaine use dropped by about 32%, and past month use decreased by about 29%. Cocaine seizures were shown to decrease by 22%, prices doubled, and purity dropped by 35%. With increased regulation the U.S. government was indicating that they may increase surveillance which logically leads to the increase in cocaine seizures. The increase in cocaine price follows standard economic thought, when inputs to manufacturing increase prices are expected to increase. Purity decreasing is potentially a result of cocaine manufacturers reacting to an increase in cost and barriers to sodium permanganate by adding cheaper substances to increase the amount of cocaine. The regulation's impact on cocaine-related overdoses has not been investigated. With fewer individuals using cocaine, it is logical to anticipate a decrease in overdoses related to cocaine. However, with purity decreasing as well over the period, it is possible that this results in an increase in overdoses related to cocaine. Further, people who use drugs will often switch to another illicit drug should availability become limited, potentially increasing use and overdose related to other substances.

In this study, we add to the literature by using representative state-level data on past year and lifetime drug use and overdose deaths related to each substance to identify the impact of sodium permanganate regulation.

## 3.2 Data

To estimate the impact of sodium permanganate regulation, we leverage several data sources to measure past year and past month illicit drug use and substance-specific fatal overdoses. These datasets provide state-level information, and all analyses are conducted at this level.

We use the National Survey on Drug Use and Health (NSDUH) to measure illicit drug use. Sponsored by the Substance Abuse and Mental Health Services Administration (SAMHSA), the NSDUH is a nationally representative survey and the largest annual survey on substance use in the United States. NSDUH gathers self-reported use of illicit drugs in the respondent's lifetime and the past year. The NSDUH data are available in two-year increments: 2002-2003, 2004-2005, 2006-2007, 2008-2009, 2010-2011, 2012-

2013, 2014-2015. While self-reported drug use is subject to underreporting, the NSDUH offers the participants a private and confidential method of responding to these sensitive questions.

Illicit drug overdose deaths were collected through the Centers for Disease Control and Prevention (CDC) on CDC Wonder. Drug overdose deaths were classified using the ICD-10 underlying cause of death codes X40-44 (unintentional), X60-64(suicide), X85 (homicide), or Y10-Y14 (undetermined intent). Among deaths with drug overdose as the underlying cause, the type of drug involved is indicated by ICD-10 codes T40 (opioids), T40.1 (heroin), T40.4 (synthetic opioids), and T40.5 (cocaine).

State demographics were retrieved from the National Center for Health Statistics.

Table 1 presents the descriptive statistics for the pre-regulation and post-regulation periods

**Table 1: Descriptive Statistics**

| | Pre-Regulation (2004-2006) | Post-Regulation (2007-2015) |
|---|---|---|
| Percent White | 80.76% | 79.38% |
| Percent Black | 13.33% | 13.77% |
| Percent Other | 5.91% | 6.85% |
| Percent Male | 49.12% | 46.17% |
| Percent Female | 50.88% | 50.83% |
| Unemployment Rate | 5.08 | 7.22 |
| Stimulant Deaths | 115.20 | 157.85 |
| Cocaine Use past year | 242665.40 | 209643.20 |

## 3.3 Empirical Strategy

A dose-response model was used to identify the effects on illicit drug outcomes due to the regulation of sodium permanganate, utilizing the pre-regulation variation in cocaine use across states. The dose-response approach is similar to a difference-in-differences design but simultaneously compares treatment exposure levels across all states rather than relying on differences between treatment and control. The variation in cocaine use across states is leveraged to deduce the change in illicit drug outcomes. Using ordinary least squares (OLS) we estimate the following equation:

$$Y_{sy} = \gamma_0 + \beta_1 Post_y + \beta_2 Pre_s \times Post_s + \beta_3 Pre_s^2 \times Post_s + \beta_4 Oxy_s Y_y + \delta_{sy} + \varepsilon_{sy}$$

Where $Y_{sy}$ are illicit drug outcome including drug poisonings, past year use, and lifetime use during time y in state s. Post is the post-regulation period indicator, activating after 2006. $Pre_s$ is the mean state cocaine use before the regulation. $Y_y$ are time fixed effects, $\delta_{sy}$ contain state-time controls for demographics and unemployment. The main coefficient of interest is $\beta_2$. This coefficient represents the effect of the regulation by differencing outcomes across states with differing cocaine use before the regulation. $Pre^2$ is the pre-regulation cocaine use variable squared. $Oxy_s$ is pre-regulation OxyContin use in state s.

The outcomes examined in our models are cocaine deaths, cocaine use, methamphetamine use, heroin use, and heroin deaths.

## 3.4 Results

First, we graphically show that cocaine use in a state strongly predicts changes in cocaine use after the enforced regulation. Figure 1 shows the relationship between pre-regulation cocaine use and the change in cocaine use from the pre to the post-period. States are divided into quintiles based on their pre-regulation cocaine use (2002-2005). We observe a greater change in cocaine use in states that started with a higher use rate. States with higher initial cocaine use saw a 27% and 19% decrease in cocaine use after the regulation.

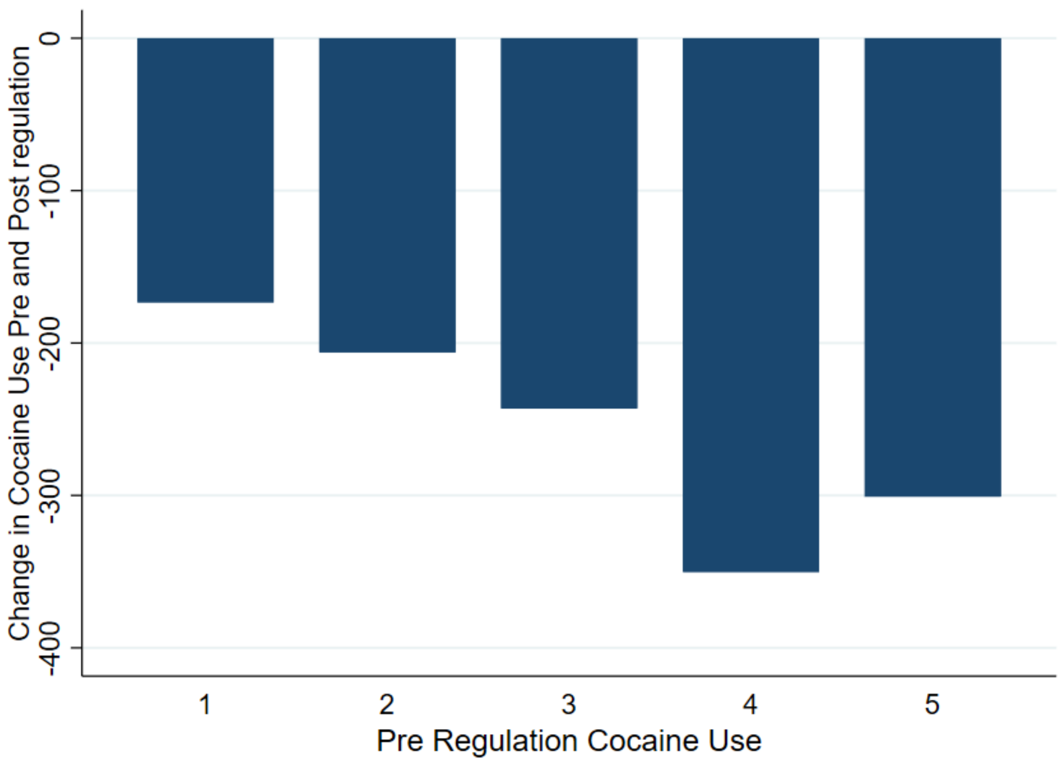
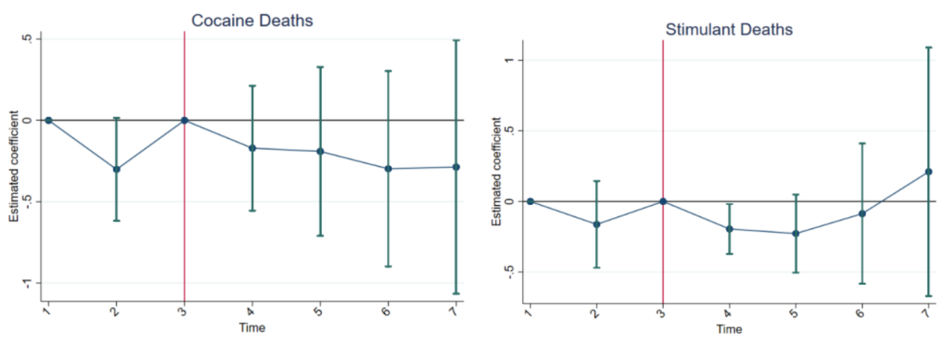



**Figure 1: Pre-regulation Cocaine Use and Change Between Pre and Post**

*Notes: Quintiles represent states with the lowest to highest pre-regulation cocaine use. The change in cocaine use is weighted by population.*

Next, we identify if the change in cocaine use led to changes in cocaine, heroin, stimulant, and all drug deaths, as well as cocaine use, heroin use, methamphetamine use, and stimulant use. Presented in Figure 2 is the full set of coefficients from estimating our event-study model for specific drug mortality. The first graph in Figure 4A shows the estimates and 95% confidence intervals for cocaine mortality. The effect of cocaine regulation had a sharp, statistically insignificant decrease in cocaine deaths for a few years before flattening. Stimulant deaths decreased following the regulation before increasing to levels above 2006. Heroin and all drug deaths followed a similar trajectory of increasing immediately following the regulation before decreasing in later periods.

**A: Cocaine and Stimulant Mortality**




**B: Heroin and All Drug Mortality**

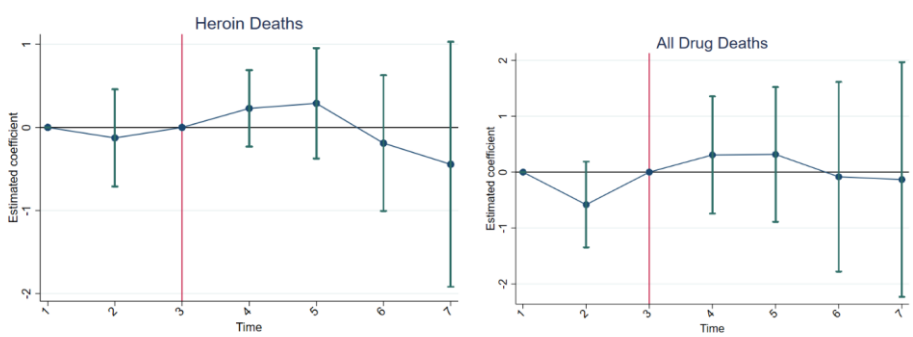
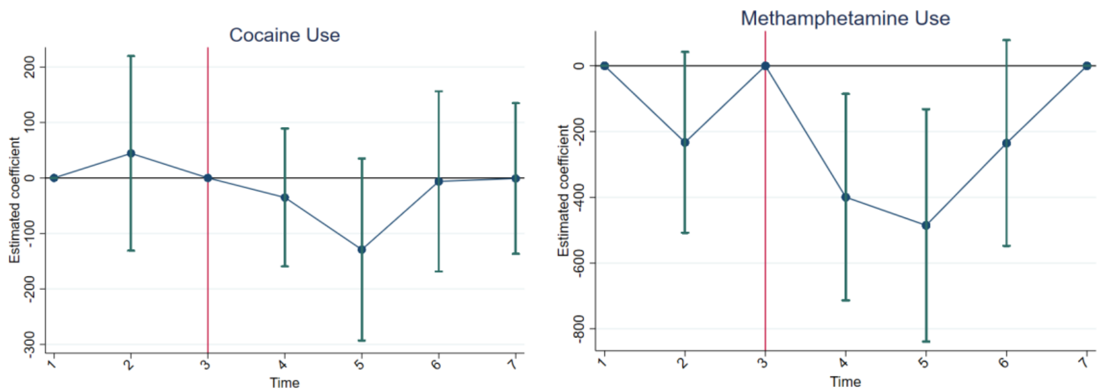



**Figure 2: Effect of Sodium Permanganate Regulation on Overdose Mortality – Event Study**

*Notes: The graphs include point estimates from event study and 95 percent confidence intervals, adjusted for within-state clustering*

Figure 3 presents the coefficients from estimating our models for specific drug use behavior. Cocaine use decreased for the two periods before increasing to similar levels as before the regulation. Methamphetamine and stimulant use decrease sharply immediately following the regulation before increasing to pre-regulation levels. Heroin use stayed fairly constant after the regulation with minimal fluctuations.

**A: Past Year Cocaine Use and Lifetime Methamphetamine Use**




**B: Lifetime Heroin Use and Past Year Stimulant Use**

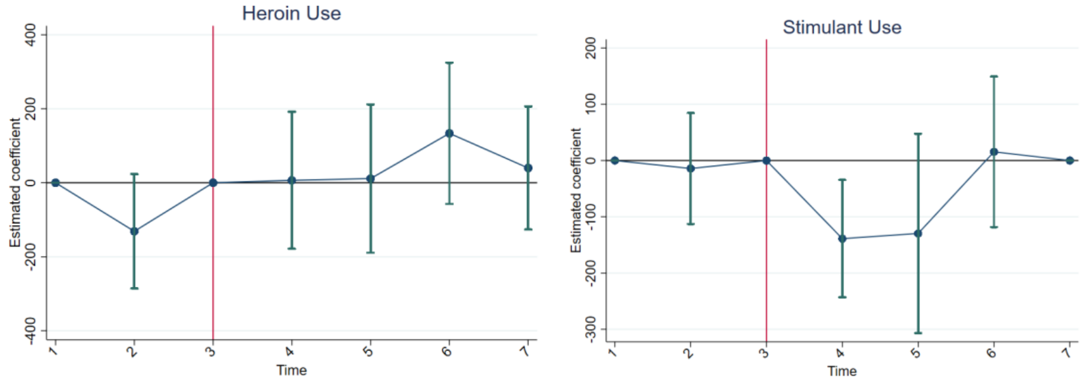



**Figure 3: Effect of Sodium Permanganate Regulation on Drug Use – Event Study**

*Notes: The graphs include point estimates from event study and 95 percent confidence intervals, adjusted for within-state clustering*

In Table 2, we present the estimates quantifying the impact of sodium permanganate regulation on drug use outcomes. Standard errors in Table 2 are clustered by state. We identify a significant decrease in cocaine use post-regulation of 616.35 per 100,000 individuals. The coefficient for stimulant use is negative and insignificant while the coefficient for stimulant death is positive but insignificant. Both heroin use and heroin mortality are negative, but neither are significant. While insignificant, the coefficient for methamphetamine use is negative. Lastly, all drug mortality increased by just over 5s deaths per 100,000 individuals, although this was not significant. Table 3 presents the results of drug outcome when taking quintile of initial cocaine use into account. When interacting with the pre-regulation cocaine use quintile, as the initial cocaine use quintile increases, the extent of the reduction in the change in cocaine use decreases until we get to the fifth quintile when we see a decrease in the magnitude of the effect, although it is not statistically significant.

## Table 2: Impact of Sodium Permanganate Regulation on Drug Outcomes

| Outcome | **Past Year Cocaine Use** | **Past Year Stimulant Use** | **Lifetime Heroin Use** | **Lifetime Methamphetamine Use** | **Cocaine Mortality** | **Stimulant Mortality** | **Heroin Mortality** | **All Drug Mortality** |
|---|---|---|---|---|---|---|---|---|
| Post*Initial Cocaine Use (ICU) | -616.35*<br>(330.49) | 274.84<br>(269.12) | -114.83<br>(366.57) | -113.10<br>(587.89) | 1.97<br>(1.28) | -0.78<br>(1.38) | -0.58<br>(3.58) | 5.33<br>(3.75) |
| Post*ICU$^2$ | .118.55*<br>(65.10) | -51.20<br>(53.02) | 55.54<br>(72.21) | -0.05<br>(114.63) | -0.34<br>(0.24) | 0.17<br>(0.26) | 0.12<br>(0.66) | -0.87<br>(0.24) |

*Note: Regressions include controls for race, gender, population, unemployment, county, year. Standard errors are clustered at the county level*

**Significant at 0.10 **Significant at 0.05 ***Significant at 0.001*

*The lowest quintile is the reference group*

**Table 3: Impact of Sodium Permanganate on Drug Outcome by Initial Cocaine Use Quintile**

| Pre-Regulation Use Quintile | Past Year Cocaine Use | Past Year Stimulant Use | Lifetime Heroin Use | Lifetime Methamphetamine Use | Cocaine Mortality | Stimulant Mortality | Heroin Mortality | All Drug Mortality |
|---|---|---|---|---|---|---|---|---|
| 2 | 10.50 | 30.24 | 91.63 | 22.02 | .39 | -.54 | .22 | .36 |
| | (98.04) | (80.15) | (108.09) | (173.25) | (.33) | (.35) | (.80) | (1.11) |
| 3 | -56.01 | 106.52 | -64.39 | .53 | .69* | -.33 | .35 | 1.48 |
| | (99.08) | (81.04) | (109.25) | (175.18) | (.33) | (.33) | (.81) | (1.13) |
| 4 | -171.50 | 3.08 | 68.84 | -173.70 | .68* | -.23 | .13 | 1.80 |
| | (-98.00) | (80.00) | (108.05) | (172.92) | (.33) | (.41) | (.88) | (1.11) |
| 5 | -15.35 | 53.19 | 293.03*** | -177.58 | .40 | -.07 | .17 | .94 |
| | (101.64) | (83.05) | (112.07) | (179.47) | (.33) | (.33) | (.76) | (1.16) |

*Note: Regressions include controls for race, gender, population, unemployment, county, year. Standard errors are clustered at the county level*

**Significant at 0.10 **Significant at 0.05 ***Significant at 0.001*

*The lowest quintile is the reference group*

## 3.5 Robustness

While the results from the original analysis provides important insight, it is necessary to consider additional robustness tests to assess the reliability of the findings. As a robustness check I interacted the mean pre-regulation cocaine deaths in each state with the post time period instead of cocaine usage. Mortality was used due to less reporting bias being in the variable. Drug use is self-reported by people who use drugs, and while the NSDUH attempts to provide a safe, non-judgmental environment, topics such as drug use are frequently underreported. Table 4 presents the results of the robustness check. Past year cocaine use and cocaine mortality are decreasing, however the effects are now insignificant. Heroin use significantly decreased by 182.50 per 100,000 while heroin mortality insignificantly increased. In this model stimulant use decreased by 171.83 per 100,000 while stimulant mortality increased by 0.48 per 100,000. Methamphetamine use and all drug mortality are still both insignificant. While there were some variables that changed signed and became significantly affected, all point estimates fall within the confidence interval of the original model, suggesting it holds up to the robustness check.

**Table 4: Impact of Initial Cocaine Death Rates on Drug Outcomes**

| Outcome | **Cocaine Use** | **Cocaine Mortality** | **Heroin Use** | **Heroin Mortality** | **Stimulant Use** | **Stimulant Mortality** | **Methamphetamine Use** | **All Drug Mortality** |
|---|---|---|---|---|---|---|---|---|
| Post*Initial Cocaine Mortality (ICM) | -10.76<br>(67.34) | -0.20<br>(0.22) | -182.50***<br>(67.08) | 0.15<br>(0.58) | -171.83***<br>(49.66) | 0.48**<br>(0.23) | 148.56<br>(108.86) | -0.15<br>(0.86) |
| Post*ICM$^2$ | -5.60<br>(11.14) | 0.06*<br>(0.04) | 14.05<br>(11.10) | -0.03<br>(0.08) | 29.24**<br>(8.21) | -0.08**<br>(0.04) | -3.39<br>(18.00) | -0.03<br>(0.14) |

*Note: Regressions include controls for race, gender, population, unemployment, county, year. Standard errors are clustered at the county level*

**Significant at 0.10 **Significant at 0.05 ***Significant at 0.001*

*The lowest quintile is the reference group*

## 3.6 Discussion

We examined the effects of a federal regulation of sodium permanganate, a vital component in the manufacturing of cocaine. We identified an insignificant decrease in past year cocaine use and lifetime methamphetamine use and an insignificant increase in cocaine mortality, past year stimulant use, and stimulant mortality. A significant increase in lifetime heroin use and all drug mortality was also identified.

Prior literature on this utilized time-series analysis to estimate the effects of sodium permanganate regulation, while we leveraged the effects across states based on pre-regulation cocaine use. Overall, we identify a 22% decrease in cocaine use post-regulation, which was significant.

The results of this study suggest that supply-side interventions can be effective. Cocaine use significantly decreased, heroin use and methamphetamine use both decreased, although not significantly.

Further, all drug policies potentially have different effects in the short run and long run. Over time, suppliers may introduce different substances to reduce costs, increase potency, and alter the drug distribution system. This is evident with the introduction of fentanyl into the drug supply, increasing overdose fatality. Our study groups all of the years' post-regulation into one group, limiting the identification of the long-run efficacy of the policy. Further studies need to look at the policy's effects on deterring future drug use.

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