ON YOUR SIDE? THE EFFECTS OF GOOD SAMARITAN LAWS, DRUG-INDUCED HOMICIDE LAWS, AND NALOXONE ACCESS LAWS ON OPIOID-RELATED DEATHS

A Thesis
Submitted to the Graduate Faculty
of the
North Dakota State University
of Agriculture and Applied Science

By

Richard Feir

In Partial Fulfillment of the Requirements
for the Degree of
MASTER OF SCIENCE

Major Department:
Agribusiness and Applied Economics

April 2024

Fargo, North Dakota

North Dakota State University
Graduate School

Title

ON YOUR SIDE? THE EFFECTS OF GOOD SAMARITAN LAWS, DRUG-INDUCED HOMICIDE LAWS, AND NALOXONE ACCESS LAWS ON OPIOID-RELATED DEATHS

By

Richard Feir

The Supervisory Committee certifies that this ***disquisition*** complies with North Dakota State University's regulations and meets the accepted standards for the degree of

MASTER OF SCIENCE

SUPERVISORY COMMITTEE:

Raymond March, Ph.D.
Chair

Veeshan Rayamajhee, Ph.D.

Kerianne Lawson, Ph.D.

Glenn Furton, Ph.D.

Approved:

05/02/2024
Date

Cheryl Wachenheim, Ph.D.
Department Chair

ABSTRACT

I examine the effects of Good Samaritan laws (GSLs), drug-induced homicide laws (DIH laws), and naloxone access laws (NALs) on opioid-related deaths. Using a fixed effects OLS and Poisson approach similar to Rees et al. (2019), I find significant negative correlation early adopting NAL states, but significant positive correlation among later states. Parsing timespans by NAL enactment supports these results. DIH law coefficients are consistently positive and often significant across models and timespans. GSLs, when interacted with DIH laws, have a negative significant coefficient. When specifying GSLs to include only those states that have no DIH law, significance and negative magnitude increase. This continues when specifying GSLs whereby the bystander and victim are both protected and further when specified not to include GSLs which provide parole or probation protections. Generally, DIH laws and NALs are correlated with an increase in opioid-related deaths while GSLs are correlated with a decrease.

ACKNOWLEDGMENTS

I would like to thank Dr. Raymond March, Dr. Veeshan Rayamajhee, Dr. Kerianne Lawson, and Dr. Glenn Furton for taking the time to offer feedback and support as I completed my thesis. I'm especially thankful for Dr. March and Dr. Rayamajhee, who responded to emails I sent spurred by a crisis of faith in econometric methods.

I'd like to thank my wife, Julianne, who is always supportive, cares for our two sons, and has provided me the time to complete this degree. Whatever work ethic, intelligence, and creativity I have, I credit to God and the support of family, friends, and teachers. I thank all of you for your kindness in my life.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDIX TABLES

LIST OF APPENDIX FIGURES

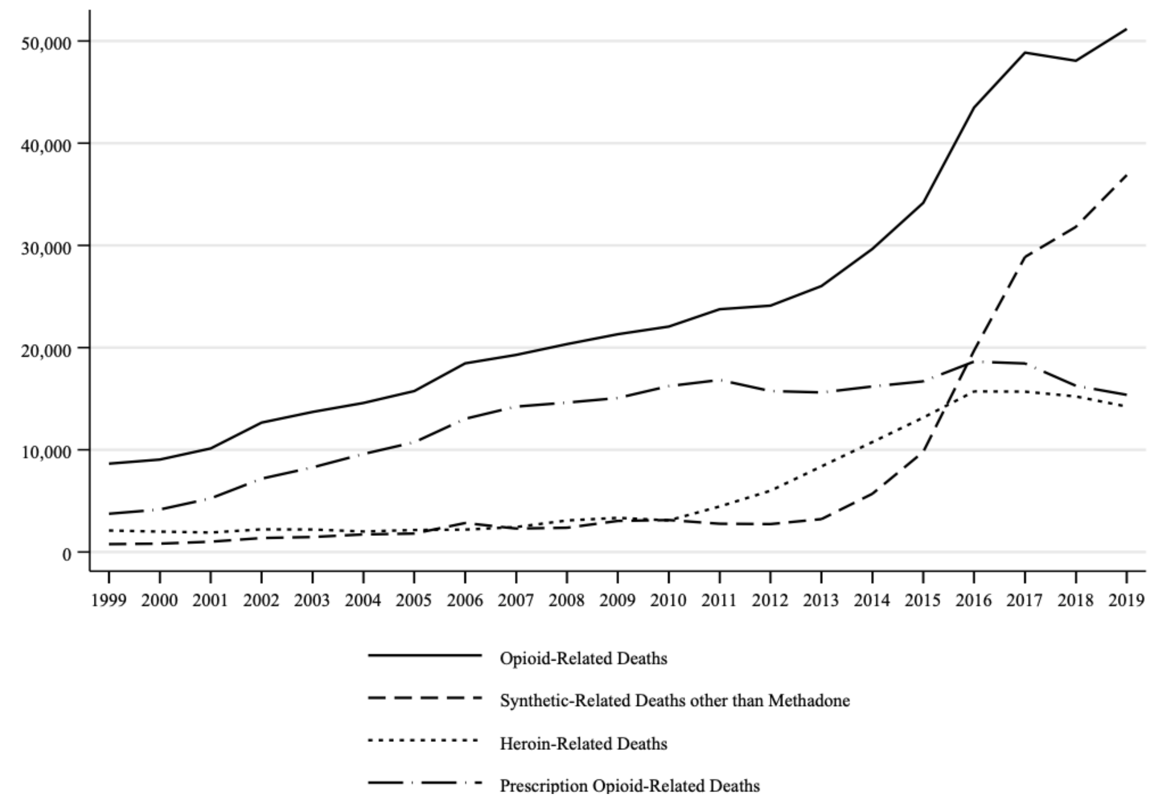
1. INTRODUCTION

1.1. Background

Since 1999, over 654,000 people in the US have died from opioid-related overdoses (CDC, 2023b). In 2021, approximately 107,000 individuals died of drug overdoses in the US. Nearly 75 percent of these fatalities were associated with opioid misuse (CDC, 2023b). The CDC (2023b) traces the beginning of widespread opioid misuse (and the origins of the opioid crisis) to 1999, in which as legally prescribed opioids and opioid-related overdoses concurrently increased. These and other noteworthy trends are displayed in Figure 1.[1]

Figure 1

Opioid-Related Deaths, 1999-2019



[1] Data used to compile Figure 1 is from the CDC's Wonder Database.

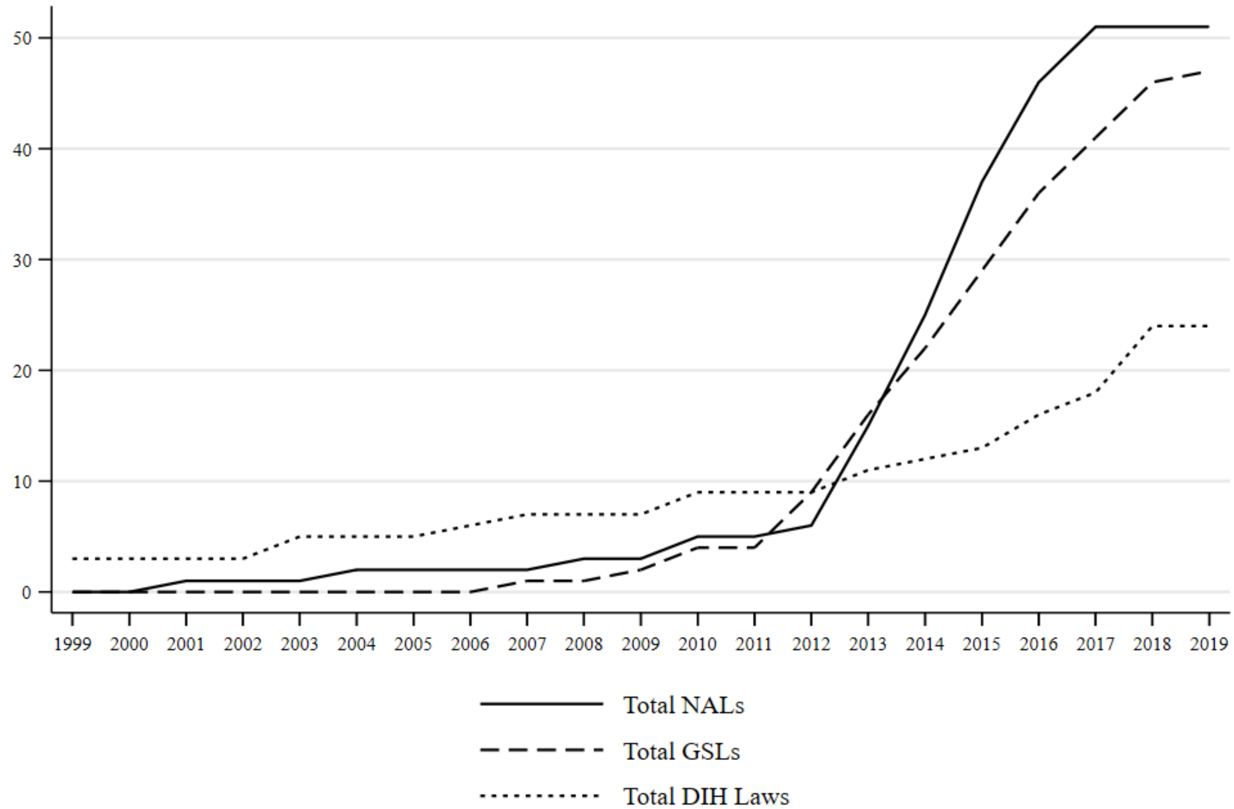
Heroin deaths assumed an increasing role in raising opioid-related deaths in 2010. This is largely attributed to the reformulation of OxyContin to reduce intravenous and insufflation abuse and increased presence of prescription drug monitoring programs (hereafter PDMPs), which tightened the supply of prescribed opioids (Beachler et al., 2022; Rees et al., 2019). These changes led many addicts to use heroin as a substitute (Bennett et al., 2011; Erfanian et al., 2019; Kim, 2021). In 2013, synthetic opioid-related deaths increased rapidly, and became the largest cause of opioid-related deaths in 2016. While purchasing is difficult to quantify due to the illicit nature of drug use, analysis of opioid-related deaths seems to reveal that synthetics have become the most popular substitute for both heroin and prescription opioids. These synthetic opioids, including fentanyl, can be manufactured at lower costs, have much higher strength than prescribed opioids, and up to 50 times higher strength than heroin (CDC, 2023; O'Brien & Wernau, 2023).

Hoping to reduce opioid-related fatalities and other adverse consequences of the opioid epidemic, states enacted several forms of policies. Some newer policies include PDMPs and naloxone access laws (hereafter NALs). PDMPs collect prescription information to reduce the misuse of controlled medicines (PADPS, 2016). NALs allow licensed health care providers to prescribe and distribute naloxone hydrochloride, which has the ability to reverse opioid overdoses (PDAPS, 2022a).

States also adopted Good Samaritan Laws (hereafter GSLs) and drug-induced homicide laws (hereafter DIH laws) in hopes of addressing the causes of opioid-related deaths. GSLs provide immunity or legal protection for people who contact emergency services in the event of an overdose (PDAPS, 2022b). DIH laws establish criminal liability for individuals who provide controlled substances to someone else which results in death (PDAPS, 2019). Figure 2 shows the total number of these laws passed by states over time.[2]

Figure 2

Law Enactment, 1999-2019



In relation to the opioid epidemic, PDMPs exist to reduce prescribed opioids in hopes of reducing the amount of supply available to be abused, thereby reducing overdoses. NALs exist to prevent opioid overdoses from leading to death by allowing access to naloxone for reversing overdoses. GSLs exist to encourage bystanders to call emergency services in the event of witnessing an overdose so that medical care, like naloxone deployment, can prevent overdoses

---

[2] This chart shows the total number of laws which have been enacted for at least half a year within each U.S. state and D.C. Data was obtained from the Prescription Drug Abuse Policy System (PDAPS, 2019, 2022, 2023).

from leading to death. DIH laws exist to provide greater levels of penalty for drug dealers, in hopes that, as the risk of engaging in illicit activity increases, the number of drug dealers will decrease, thereby decreasing the supply of illicit substances.

1.2. Objectives

This paper seeks to analyze the effects of GSLs, DIH laws, and NALs on opioid-related deaths from 1999 to 2019.[3] Following Rees et al. (2019), I perform fixed effects OLS and Poisson regressions with an extended timespan, state-level DIH measures, and interaction terms.

My analysis finds that NALs lead to decreases in opioid-related deaths in early adopting states, but in total, have since continued to show positive and significant effects on opioid-related deaths. I also find strong evidence that DIH laws reduce the effects of GSLs. Specifically, when DIH laws and GSLs are interacted, GSLs are associated with a 12 percent decrease in opioid-related deaths and the interaction term is associated with a 1 percent increase. By creating one term for GSLs in states with no DIH law, this combined term is associated with a 11 percent decrease in opioid-related deaths. As heterogeneity is accounted for in GSLs in states with no DIH law, those which protect victim and bystander are associated with a 13 percent decrease in opioid-related deaths and those which do not provide additional protections for parole or probation violations are associated with an 18 percent decrease in opioid-related deaths. DIH laws tend to have a positive and statistically significant coefficient among many timespan selections and models.

[3] While some data is available through 2020, I do not extend my analysis to include years impacted by the Covid-19 pandemic due to state-level heterogeneity in pandemic responses.

1.3. Organization

This paper proceeds as follows. Section 2 reviews the relevant public health and economics literature on the evolution and effects of overdose-related laws, including PDMPs, NALs, GSLs, and DIH laws. Section 3 reviews my data and empirical approach. Section 4 provides primary findings from the analysis. Section 5 concludes and provides suggestions for future research.

2. LITERATURE REVIEW

In analyzing the effects of GSLs, DIH laws, and NALs, it's necessary to account for differences in the legal environment across the United States. Analyzing these laws and PDMPs builds understanding of the changes of the opioid epidemic, state-level responses, and how these laws might interact. Therefore, I review each of them in the subsections that follow.

2.1. PDMP and Opioid Use

Powell, et al. (2020), found A 10 percent increase in the opioid medical supply results in a 7.1 percent increase in opioid-related deaths among Medicare-ineligible population. Kim (2021) utilized difference-in-differences to determine that, after two years of implementation, must-access PDMPs were associated with 0.9 more heroin deaths per 100,000, in half-year periods above control states. Rees et al. (2019) agree with this finding that a tightening of the supply of licit drugs through PDMPs may have led users to turn to illicit substances such as heroin. Synthetic opioids may act as a more recent substitute drug. Since GSLs aim to protect illicit drug users, this existing literature on PDMPs suggest that GSLs may be more effective in the era of synthetic opioids.

2.2. NALs

Perhaps the earliest and most influential paper examining NALs, GSLs, and their effect on opioid fatalities is Rees et al. (2019). This paper found the adoption of a NAL was associated with a statistically significant 9-10 percent reduction in opioid-related deaths. However, this effect is driven by states which passed NAL legislation prior to 2011 (Rees, et al., 2019). Focusing on the effects of a naloxone distribution program, Bennet et al. (2011) find in a survey that 89 of 426 individuals who were given and trained to use naloxone, reported that, of 249 overdose episodes in which naloxone was administered, 96 percent were reversed. While

Tabatabai et al. (2023) find NALs and GSLs to have a significant negative impact on synthetic opioid overdose death rates, Doleac & Mukherjee (2022) find insignificant results.

2.3. GSLs and DIH Laws

Hamilton et al. (2021) find that opioid overdose death rate reduction from GSLs that have been in effect for two years compared to states with no law using hierarchical Bayesian spatiotemporal Poisson models. This paper concludes that GSLs with more expansive legal protections are more effective at reducing opioid overdose deaths. Additionally, GSLs are made more effective when paired with naloxone access laws and over time. The confidence intervals for these results show statistical significance with all overdose deaths and have lower confidence in opioid-specific overdose deaths. (Hamilton et al., 2021).

While insightful, both analyses have shortcomings. Rees et al. (2019) include GSLs as a binary variable, and only examine state trends up to the year 2014. By 2014, the Network for Public Health Law (2023a) finds only 23 states passed GSLs. Additionally, since the first GSL was enacted in 2007 by New Mexico, this is a short time span. Currently, 47 states and Washington DC passed GSLs (Lieberman & Davis, 2023a). Further, GSLs vary considerably in their legal protection, application to potential overdoses, and other extenuating circumstances. These factors make GSL effects potentially ill-suited to be captured by a binary variable. Hamilton addresses the heterogeneity of GSLs, but only finds significance when lagged by two years. Additionally, only the effects of GSLs with an active NAL were found, leaving GSL uncertainty regarding the individual effect of GSLs.

I contribute to the previous literature examining the policy response effectiveness of GSLs specifically and in addressing the opioid epidemic more broadly by assessing the interaction of GSLs with DIH laws and by accounting for heterogeneity among GSLs' protective features. Because GSLs serve to reduce the risk of bystanders to contact emergency services, but DIH laws increase penalties for illicit drug distribution, and thereby risk, I account for the individual and joint effects of each.

Whether GSLs effectively reduce opioid overdose mortality rates or promulgate unintended consequences largely depends on caller (Samaritan) comfortability with naloxone use, calling 911, and first-responder awareness of GSLs—which are both empirical questions (Seal et al., 2003).[4] Determining which aspects of GSLs are effective in reducing opioid-related deaths further informs policymakers and researchers more broadly whether GSLs, and what aspects of GSLs, serve their intended purpose.

[4] Measurement of these effects is further complicated by limiting county data to show different effects of state law by local demographic variables.

3. DATA AND EMPIRICAL STRATEGY

Individuals act in their own self-interest. Individuals are influenced by incentives. When a bystander sees someone experiencing overdose symptoms, they will weigh the benefits and cost, including risk, of calling 911. If there is no GSL or if a DIH has increased the perceived risk of a potential caller, they may call on the victim's phone and leave the premises. This puts responders in a difficult situation trying to find the overdose victim. The reported address could be incorrect or the exact location within an apartment may be difficult to find. If there is no one present to respond to the knocking on the door from an EMT and it is locked, the victim likely will not have naloxone administered to reverse the overdose (This American Life, 2023).

In these scenarios, the marginal cost to gain access to the door and administer naloxone is low. But without someone present to open that door, victims are unable to have the overdose reversed. The marginal benefit of whatever laws necessary to incentivize a bystander to stay may often be human lives. The fear of prosecution which could lead the bystanders to leave the victim increases the victim's likelihood of death. If the bystander sold drugs or provided drugs to a victim and the state has a DIH law, they may avoid calling 911 in fear of prosecution for homicide should the overdose victim die (Beletsky, 2019). These individuals may not be responsive to GSLs with high levels of protections due to the nullifying effect a DIH law may have on a GSL. However, a GSL with a high level of protection, and no DIH law, should incentivize more bystanders to call 911 due to the decrease in personal cost and risk.

To examine these considerations empirically, I follow the empirical approach used by Rees et al. (2019) represented in Equation (1):

$$ln(\text{Opioid Mortality Rate}_{st}) = \beta_0 + \beta_1 GSL_{st} + \beta_2 DIH_{st} + \beta_3 NAL_{st} + X_{st}\delta + v_s + w_t + u_{st} \tag{1}$$

Here, $ln(\text{Opioid Mortality Rate}_{\text{st}})$ represents the log of the opioid overdose rate per 100,000 persons in state *s* and year *t*. My variables of interest are GSL_{st}, DIH_{st}, and NAL_{st} which represents the presence of a GSL, DIH law, or NAL for at least half a year with a value of 1 and absence with 0 at time *t* and in state *s*. State heteroskedasticity is mitigated with the inclusion of a state fixed effects variable, v_s. Shock effects and trend effects, such as the heroin epidemic are mitigated with w_t to account for time fixed effects. For the baseline regressions, I include the natural log of state population and a population weight.

My recommended model is the Poisson regression due to the positive and discrete opioid deaths variable which skews rightward, random event generating qualities of overdoses, and its ability to accommodate fixed effects without the incidental-parameters problem (Rees et al., 2019). Additionally, unlike the OLS, Poisson regressions can represent nonlinear relationships (Wooldridge, 2002). Each Poisson regression uses the count of opioid-related deaths, rather than a rate per 100,000 as the dependent variable. My Poisson model is represented in Equation (2):

$$Opioid\ Deaths_{st} = E_{st}exp(\alpha_0 + \alpha_1 GSL + \alpha_2 DIH_{st} + \alpha_3 NAL_{st} + X_{st}\delta + \nu_s + \omega_t + \mu_{st}) \tag{2}$$

In Equations (1) and (2), the term X_{st} represents the inclusion of control variables. The baseline models exclude them. Control variables include an indicator for whether a PDMP was enacted for at least half the year, an indicator for whether a medical marijuana was legal (MML) for at least half the year, the natural log of sworn police officers per capita, the natural log of the beer tax, the natural log of the cigarette tax, the natural log of the percentage of the state population with a bachelor’s degree, the natural log of per capita income, the natural log of the unemployment rate, and the natural log of the effective minimum wage. I used 2019 as a base year to adjust for inflation for tax and income covariates. Like the baseline models, complete models also include the natural log of population and a population weight. Standard errors are clustered to account for heteroskedasticity and serial correlation in the error term over time (Bertrand et al., 2004; Rees et al., 2019).

The dependent variables, opioid death rate and opioid deaths were obtained using CDC Wonder database (CDC, n.d.). GSLs, DIH laws, and NALs were obtained from the Prescription Drug Abuse Policy System (PDAPS, 2019, 2022, 2023). PDMPs were also obtained from the Prescription Drug Abuse Policy System (PDAPS, 2016, 2017b). The only state without a prescription drug monitoring program at the time of that database was Missouri, which has since signed a program into law outside the time of study (Official Missouri State Website, 2021). Medical marijuana law presence was obtained from the Prescription Drug Abuse Policy System (2017a) and the National Conference of State Legislatures (2022). Sworn police officers per capita was obtained from the Bureau of Justice Statistics (n.d.-a, n.d.-b). The beer tax was obtained from Tax Policy Center (2023). The cigarette tax was obtained from the CDC (2023). The percentage of the state population with a bachelor's degree was obtained from the Census Bureau from 1999 to 2005 (2023) and from FRED for 2006 to 2019 (n.d.). Per capita income was obtained from the Bureau of Economic Analysis (2024). The unemployment rate was obtained from State and Regional Unemployment tables from the Bureau of Labor Statistics (2001, 2002, 2004, 2006, 2008, 2010, 2012, 2014, 2018). The effective minimum wage was obtained from the U.S. Department of Labor (2024). Lastly, population estimates were obtained from the U.S. Census Bureau (n.d.-a, n.d.-b, n.d.-d). Summary statistics are provided in Table 1. It includes combined variables which are included in the results section.

Table 1

Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
Ln(Opioid Mortality Rate)	1.866	0.792	-1.863	3.862
Opioid Deaths	481.12	598.571	1	4379
GSL	0.241	0.428	0	1
DIH	0.186	0.389	0	1
NAL	0.289	0.453	0	1
PDMP	0.489	0.500	0	1
MML	0.315	0.465	0	1
Ln(Police Per Capita)	0.797	0.248	0.046	1.926
Ln(Beer Tax)	-1.405	0.814	-3.912	0.477
Ln(Cigarette Tax)	-.046	0.900	-3.386	1.598
Ln(College Graduates)	-1.281	0.210	-1.89	-0.504
Ln(Per Capita Income)	10.765	0.170	10.367	11.346
Ln(Unemployment Rate)	1.636	0.345	0.789	2.617
Ln(Minimum Wage)	2.085	0.126	1.849	2.639
Ln(Population)	15.103	1.034	13.106	17.49
GSL with Bystander and Victim Protections	0.227	0.419	0	1
GSL × Controlled Substance Possessions	0.217	0.412	0	1
GSL × Paraphernalia Possessions	0.140	0.347	0	1
GSL × Parole or Probation Protections	0.096	0.295	0	1
GSL × Mitigating Factors	0.135	0.341	0	1
GSL with no DIH	0.158	0.365	0	1
GSL with Bystander and Victim and no DIH	0.148	0.355	0	1
GSL with Bystander and Victim and no DIH or Parole or Probation Protections	0.105	0.306	0	1

4. RESULTS

Table 2 reports the baseline and complete estimates for Equations (1) and (2).

Table 2

OLS & Poisson, 1999-2019

	OLS Baseline	Poisson Baseline	OLS	Poisson
GSL	-0.023	-0.061	-0.050	-0.085
	(0.086)	(0.091)	(0.087)	(0.084)
DIH	0.173	0.253**	0.094	0.107*
	(0.103)	(0.104)	(0.078)	(0.057)
NAL	-0.006	0.143***	-0.049	0.069
	(0.049)	(0.056)	(0.051)	(0.050)
PDMP			0.013	-0.091
			(0.066)	(0.063)
MML			0.148*	0.224***
			(0.083)	(0.063)
Ln(Police Per Capita)			0.267	-0.093
			(0.397)	(0.243)
Ln(Beer Tax)			0.082	0.059
			(0.088)	(0.066)
Ln(Cigarette Tax)			0.070	0.079
			(0.055)	(0.055)
Ln(College Graduates)			-0.091	0.045
			(0.248)	(0.217)
Ln(Per Capita Income)			-1.370	-2.320**
			(0.969)	(1.075)
Ln(Unemployment Rate)			-0.076	-0.246
			(0.165)	(0.181)
Ln(Minimum Wage)			-0.638**	-0.357*
			(0.249)	(0.191)
Ln(Population)	-3.701***	-3.204***	-3.574***	-2.499***
	(0.647)	(0.853)	(0.634)	(0.882)
Constant	56.831***	53.408***	70.318***	68.254***
	(9.881)	(13.043)	(15.607)	(20.581)
Observations	1,071	1,071	1,071	1,071
R-squared	0.838		0.849	

Standard errors corrected for clustering at the state level in parentheses

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

Table 2 reveals a non-statistically significant relationship for NAL's and GSL's impact on opioid overdose deaths for both the Poisson and OLS regressions. DIH laws show robust results, usually showing significance regardless of year selection and a substantial positive coefficient. This provides suggestive evidence that DIH Laws provide some understanding as to why GSLs do not have significance from 1999 through 2019. Explanation for the lack of significance for NALs is found in Tables 3 and 4.

Table 3

Early, Mid-, and Late Adopting NAL States, 1999-2019

	OLS	Poisson
Early adopting states (1999-2010)	-0.410***	-0.309***
	(0.063)	(0.060)
Mid-adopting states (2011-2012)	0.118	0.251***
	(0.124)	(0.055)
Late adopting states (2013-2019)	0.118	0.214***
	(0.085)	(0.062)
GSL	-0.001	-0.031
	(0.074)	(0.072)
DIH	0.079	0.092**
	(0.061)	(0.042)
Observations	1,071	1,071
R-squared	0.864	

Standard errors corrected for clustering at the state level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3 replicates the early, mid-, and late adopting state selection of Rees et al. and found consistent results. DIH laws continue to be significant with a positive coefficient, GSLs are insignificant, and all NAL state selections are significant at 1 percent for all Poisson regressions. In states which enacted a NAL prior to 2011, NALs are associated with a 27 percent decrease in opioid-related deaths ($e^{-.309} - 1 = -.266$). While this percentage was larger and significant at 1 percent if New York's NAL was classified as passing in 2014, as Rees et al. specified, the early states still seem to decrease rates while others increase rates. States which enacted a NAL in 2011 and 2012 are associated with a 29 percent increase in opioid-related deaths ($e^{.251} - 1 = .285$). Similarly, states which enacted a NAL after 2012 are associated with a 19 percent increase in opioid-related deaths ($e^{.214} - 1 = .193$). Therefore, regressing NAL altogether reveals insignificant results, but both positive and negative coefficients when parsed.

Table 4

Poisson Across Timespans

	1993-2003	2004-2019	1999-2004	2005-2019	1999-2007	2008-2019	1999-2008	2009-2019	1999-2010	2011-2019
GSL	0	-0.052	0	-0.043	0.115	-0.022	0.114	-0.018	-0.223***	-0.002
	(.)	(0.072)	(.)	(0.071)	(0.150)	(0.060)	(0.134)	(0.061)	(0.080)	(0.056)
DIH	0.058	0.114*	0.123	0.116**	0.177**	0.110*	0.121	0.101*	0.205**	0.091*
	(0.122)	(0.058)	(0.077)	(0.058)	(0.084)	(0.057)	(0.081)	(0.052)	(0.081)	(0.048)
NAL	-0.284**	0.145***	-0.105	0.155***	-0.244***	0.227***	-0.006	0.233***	-0.127**	0.199***
	(0.122)	(0.051)	(0.152)	(0.053)	(0.079)	(0.078)	(0.043)	(0.071)	(0.055)	(0.074)
Obs.	255	816	306	765	459	612	510	561	612	459

Standard errors corrected for clustering at the state level in parentheses

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

Table 4 provides further incite to the relationship of NAL effectiveness over time by using a Poisson regression over many timespans. The first states to enact a NAL were New Mexico (2001), Connecticut (2003), New York (2006), California (2008), Illinois (2010), and Washington (2010). When using timespans which include years leading up to and the year of an enactment of each law, results are often consistent and negative. Yet, when regressing years following the enactment of laws through 2019, results have a large magnitude and 1 percent significance. This provides further evidence that early estimates of negative NAL coefficients were caused by early adopting states. These variations in timespan provide further confidence that DIH laws increase opioid overdose mortalities due to the consistently positive and often significant coefficient despite short and varying timespans.

Table 5 reports the OLS and Poisson coefficients for Equations (1) and (2) but replaces the dummy, GSL_{st}, with five types of protections applied during the time in which a GSL was in effect.

Table 5

Heterogeneity of GSLs

	OLS	Poisson
GSL × Caller and Victim Protection	-0.240	-0.207
	(0.156)	(0.134)
GSL × Controlled Substance Possessions	0.072	0.021
	(0.126)	(0.141)
GSL × Paraphernalia Possessions	0.055	0.017
	(0.109)	(0.070)
GSL × Parole or Probation Protections	0.170	0.255***
	(0.111)	(0.066)
GSL × Mitigating Factors	0.052	0.059
	(0.113)	(0.068)
DIH	0.075	0.060
	(0.076)	(0.047)
NAL	-0.057	0.057
	(0.052)	(0.050)
Constant	66.317***	63.280***
	(13.725)	(17.638)
Observations	1,071	1,071
R-squared	0.853	

Standard errors corrected for clustering at the state level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The only significant results are found in parole or probation protections. These specifications were first enacted in 2013, and there are 114 values of 1, displaying their total combined years and states of enactment for at least half a year. These results seem to indicate that the primary specification for reducing opioid-related deaths would be protection for both the caller and victim.

Table 6 reports OLS and Poisson coefficients for Equations (1) and (2) with the addition of an interaction term. Additionally, an alternative GSL_{st} term is added and interacted with DIH which specifies GSL as only those including protections for both the overdose victim and bystander.

Table 6

Interaction of GSLs and DIH Laws

	Standard GSL		GSL with Victim and Bystander Protection	
	OLS	Poisson	OLS	Poisson
DIH	0.054	-0.017	0.017	-0.048
	(0.101)	(0.092)	(0.112)	(0.101)
GSL	-0.060	-0.108	-0.116	-0.130*
	(0.091)	(0.084)	(0.091)	(0.077)
GSL × DIH	0.058	0.024	0.027	0.010
	(0.121)	(0.111)	(0.128)	(0.108)
NAL	-0.054	0.058	-0.046	0.057
	(0.050)	(0.048)	(0.048)	(0.046)
Constant	70.478***	67.903***	69.969***	67.273***
	(15.598)	(20.110)	(14.732)	(19.191)
Observations	1,071	1,071	1,071	1,071
R-squared	0.849		0.850	

Standard errors corrected for clustering at the state level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

While OLS results are insignificant, the Poisson yields the interesting result of DIH no longer having a substantial magnitude or significance. Instead, only when accounting for protection for both victim and bystander, GSL becomes 10 percent statistically significant, correlating with a 12 percent decrease in opioid-related deaths ($e^{-.130} - 1 = -.122$). The coefficient of the interaction term in all models implies that the presence of a DIH law reduces the amount by which a GSL decreases opioid-related deaths. The interaction indicates that a GSL with no DIH law would only reduce rates by 11 percent ($e^{-.120} - 1 = -.113$), while a GSL with a DIH would reduce rates by 13 percent ($e^{-.140} - 1 = -.131$). This implies that a DIH law may be leading to increased opioid-related deaths, in part, by reducing the effectiveness of GSLs. Despite GSLs and NALs having a high correlation, this did not occur when interacting DIH with NAL.[5] These results reflect economic intuition that protections for both bystander and victim yield significant results when accounting for DIH laws due to the greater magnitude and significant coefficient.

Figure 3 reveals the number of GSLs as specified for each state and D.C. from 1999 to 2019 that were in effect for at least half a year. The gradual passage of GSLs with probation or parole protections provides confidence that the coefficients of these specified dummies on opioid-related deaths reveals a true effect rather than the effect of other state heterogenous factors, such as laws passed at similar times due to a legislative response to the opioid crisis.

[5] Table A10 in the appendix shows these results. There was 1 percent significance for an increase in opioid-related deaths with the NAL and DIH law interaction term.

Figure 3

Total Number of Specified GSLs

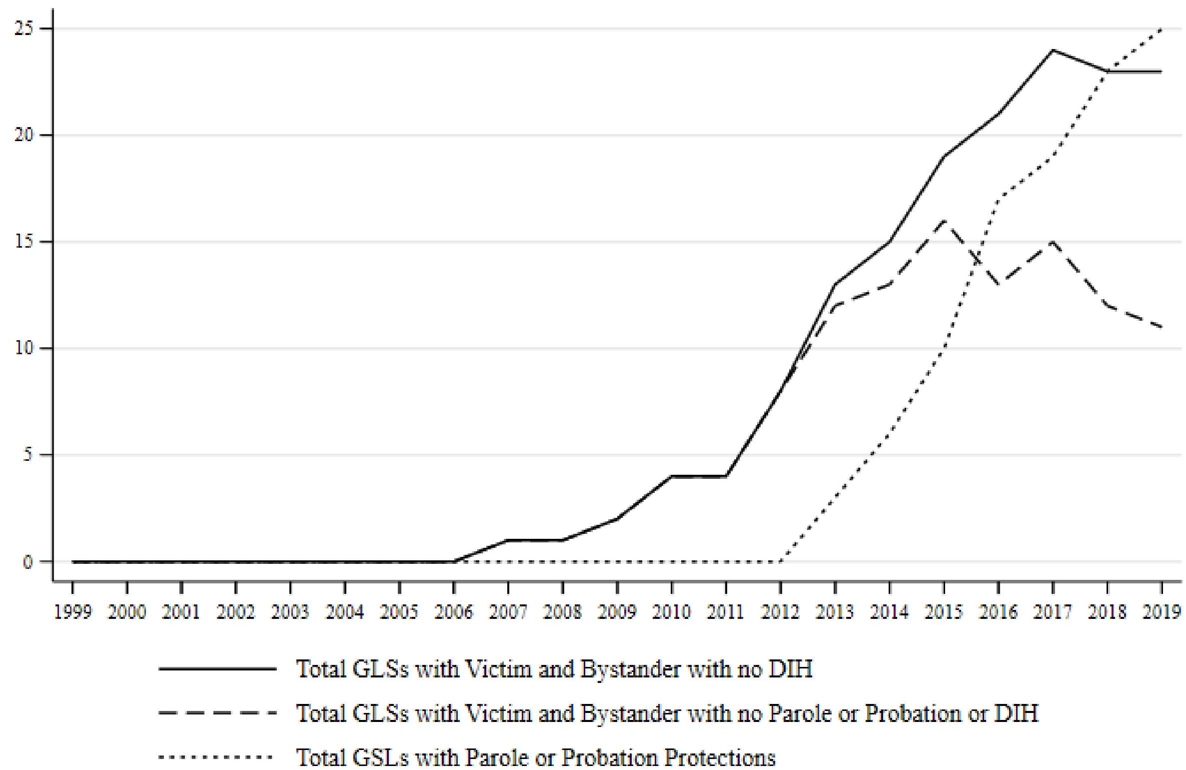


Table 7 reports the OLS and Poisson coefficients for Equations (1) and (2) but replaces the GSL_{st} term with a new specification of GSLs in which the state does not also have a DIH law, GSLs in which the state does not also have a DIH law and provides protections to both the victim and bystander, and GSLs in which the state does not have a DIH law, provides protections to both the victim and bystander, and also does not provide protections related to probation or parole.

Table 7

Effective GSLs

	OLS	Poisson	OLS	Poisson	OLS	Poisson
GSLs with no DIH Law (N = 177)	-0.083	-0.119**				
	(0.069)	(0.049)				
… and Caller and Victim Protections (N = 165)			-0.126*	-0.136***		
			(0.067)	(0.045)		
… and without Parole or Probation Protections (N = 115)					-0.170**	-0.195***
					(0.077)	(0.059)
Observations	1,071	1,071	1,071	1,071	1,071	1,071
R-squared	0.849		0.850		0.852	

Note: Since these GSLs are coded with DIHs, no DIH dummy was included in this model. N indicates the sum of laws active in all states from 1999 to 2019. In 2019, 26 states had parole or probation protections. The first GSL with this aspect was enacted in 2012. Their increase has been nearly linear.

Standard errors corrected for clustering at the state level in parentheses

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

While probation and parole specifications may warrant further attention in additional research due to their apparent moral hazard of providing additional protection to individuals who may previously have drug-related charges, the main finding of my research can be seen in the significant negative coefficients for GSLs in which there is no DIH law and both bystander and victim are protected. According to the Poisson regression, GSLs in states with no DIH law are associated with an 11 percent decrease in opioid-related deaths ($e^{-.119} - 1 = -.112$) at 5 percent significance. In the Poisson, GSLs in states with no DIH law that also provide protection for both victim and bystander are associated with a 13 percent decrease in opioid-related deaths ($e^{-.136} - 1 = -.127$) at 1 percent significance with a slightly lower but 5 percent significant OLS estimate. In the Poisson, GSLs in states with no DIH law that provide protection for both victim and bystander while not providing parole or probation protections are associated with an 18 percent decrease in opioid-related deaths ($e^{-.195} - 1 = -.177$) at 1 percent significance, with a slightly lower but 5 percent significant OLS estimate. As the GSL was specified to become specific to what intuitively follows in effectiveness, the R-value increased.

5. CONCLUSION

Opioid-related deaths in the United States continue to rise annually. This epidemic continues to evolve. The first wave, 1999-2009, was characterized by increased prescription opioids. The second wave, 2010-2012, was characterized by increased heroin use as a substitute to tightened prescription supplies. The third wave, beginning in 2013 with the rise in synthetic opioids, but not overtaking heroin or prescription opioids until 2016, has continued to characterize the crisis until recently.

The effects of GSLs, DIH laws, and NALs differ. While all these laws have the intended purpose of reducing opioid-related deaths, in practice, they have unknown or mixed results. When considering the waves of the opioid epidemic, it follows that effects of each law would change over time. Contrary to current medical efforts to make naloxone more available, it seems naloxone access laws have led to increases opioid overdose mortalities since 2004 or when excluding early adopting states. GSLs seem insignificant on their own. However, upon interacting GSLs with drug-induced homicide laws, I find that they are effective in reducing opioid overdose mortalities. Drug-induced homicide laws, while receiving little attention, show robust results in increasing opioid overdose mortalities.

Good Samaritan laws, while insignificant on their own, prove significant with negative coefficients when interacted with DIH laws. Further, specifying GSLs by aspects leads to greater significance and levels of reduction of opioid overdose deaths. Except for the specification of parole and probation protections seem to be the only protection which actually increases opioid overdose mortalities, greater protections effectively incentivize individuals to contact emergency services to reduce opioid-related deaths. When DIH laws are present, they reduce the perceived legal safety that bystanders may have. As more individuals hear of family members or friends who have been heavily prosecuted resulting from an overdose death, their willingness to rely on the legal protections provided by GSLs decreases.

Lastly, Drug-induced homicide laws, interacted with GSLs or not, increase opioid overdose mortalities. Across models and timespans, DIH laws seem to be heavily correlated with increases in opioid overdose mortalities. While part of the justification of DIH laws would be to reduce the amount of illegal activity in the long run, the opposite proves true. Table A5, in the appendix, shows that 3 or more years after a DIH law is enacted these laws are correlated at 1 percent significance with a 59 percent increase in opioid-related deaths.[6] The event studies, represented in Table A5 and Figures A1, A2, and A3 echo my findings that NALs and GSLs are correlated with increases opioid-related deaths while GSLs are correlated with decreases.

Tables 6 and 7 further confirm GSLs are correlated with decreases in opioid-related deaths, but are nullified by the inclusion of a DIH law. Additional research should continue to focus on the effects of naloxone and whether moral hazard provides complications for NALs under specific scenarios. Since DIH laws have robustly shown to be associated with increased opioid-related deaths, states should look to halt, repeal, or provide further analysis towards their effects. GSLs, which seem to have no moral hazard effects, should again be embraced by states, specified to protect both victim and bystander, and promoted by state health agencies.

Policymakers need to reconsider their approach to the opioid crisis. Naloxone is effective at reversing opioid overdoses, but it cannot reverse overdoses of non-opioids. There is growing prevalence of polydrug use, when victims use stimulants, such as methamphetamines or cocaine, or sedatives, such as xylazine, in addition to an opioid (CDC & National Center for Injury

---

[6] Figures 1-3 in the appendix show the event studies of these three laws over time.

Prevention and Control, 2024). Growing stimulant use with opioids has distinguished the "Fourth Wave" of the crisis (Ciccarone, 2021). However, most state-level efforts primarily emphasize increasing naloxone access. Similarly, states continue to enact DIH laws despite preliminary evidence against their effectiveness in reducing opioid death rates.

GSLs garner comparatively little attention despite their consistent negative correlation with opioid-related deaths when accounting for DIH laws. The provision of protection for both victim and bystander is key to their effectiveness. Protections for parole and probation offenses, while more limited in number, seem to decrease their effectiveness or even increase opioid-related deaths. Overall, my findings strongly suggest states might consider refining their approach to the crisis to include such GSLs and remove DIH laws.

REFERENCES

Anderson, D. M., Hansen, B., & Rees, D. I. (2015). Medical Marijuana Laws and Teen Marijuana Use. *American Law and Economics Review*, *17*(2), 495–528.

Beachler, D. C., Hall, K., Garg, R., Banerjee, G., Li, L., Boulanger, L., Yuce, H., & Walker, A. M. (2022). An evaluation of the effect of the oxycontin reformulation on unintentional fatal and nonfatal overdose. *The Clinical Journal of Pain*, *38*(6), 396–404.

Beletsky, L. (2019). America's favorite antidote: Drug-induced homicide in the age of the overdose crisis. *Utah L. Rev.*, 833.

Bennett, A. S., Bell, A., Tomedi, L., Hulsey, E. G., & Kral, A. H. (2011). Characteristics of an overdose prevention, response, and naloxone distribution program in Pittsburgh and Allegheny County, Pennsylvania. *Journal of Urban Health*, *88*, 1020–1030.

Bertrand, M., Duflo, E., & Mullainathan, S. (2004). How Much Should We Trust Differences-in-Differences Estimates? *The Quarterly Journal of Economics*, *119*(1), 249–275. JSTOR.

Bureau of Economic Analysis. (2024, March 29). *Regional Data | GDP and Personal Income | SASUMMARY State annual summary statistics: Personal income, GDP, consumer spending, price indexes, and employment Personal income (Millions of current dollars)*. Bureau of Economic Analysis. https://apps.bea.gov/itable/?ReqID=70&step=1&_gl=1*11yudyt*_ga*MTkyNTIyNjA5Mi4xNzEyMzY0NjA0*_ga_J4698JNNFT*MTcxMjM2NDYxNS4xLjEuMTcxMjM2NTAwNi42MC4wLjA.#eyJhcHBpZCI6NzAsInN0ZXBzIjpbMSwyOSwyNSwzMSwyNiwyNywzMF0sImRhdGEiOltbIlRhYmxlSWQiLCI2MDAiXSxbIk1ham9yX0FyZWEiLCIwIl0sWyJTdGF0ZSIsWyIwIl1dLFsiQXJlYSIsWyJYWCJdXSxbIlN0YXRpc3RpYyIsWyI1Il1dLFsiVW5pdF9vZl9tZWFzdXJlIiwiTGV2ZWxzIl0sWyJZZWFyIixbIi0xIl1dLFsiWWVhckJlZ2luIiwiLTEiXSxbIlllYXJfRW5kIiwiLTEiXV19

Bureau of Justice Statistics. (n.d.-a). *JEET Dashboard | Bureau of Justice Statistics*. BJS. Retrieved February 23, 2024, from https://bjs.ojp.gov/jeet

Bureau of Justice Statistics. (n.d.-b). *Justice Expenditure and Employment Extracts, 1999 | Bureau of Justice Statistics*. BJS. Retrieved February 23, 2024, from https://bjs.ojp.gov/library/publications/justice-expenditure-and-employment-extracts-1999

Bureau of Justice Statistics. (2024, March 1). *Over-the-Year Change in Unemployment Rates for States, 2018-2019*. U.S. Bureau of Labor Statistics. https://www.bls.gov/lau/lastch19.htm

Bureau of Labor Statistics. (2001). *State and Regional Unemployment, 2000 Annual Averages*. https://www.bls.gov/news.release/history/srgune_02232001.txt

Bureau of Labor Statistics. (2002). *State and Regional Unemployment, 2001 Annual Averages*. https://www.bls.gov/news.release/history/srgune_02222002.txt

Bureau of Labor Statistics. (2004). *State and Regional Unemployment, 2003 Annual Averages*. https://www.bls.gov/news.release/archives/srgune_02272004.pdf

Bureau of Labor Statistics. (2006). *State and Regional Unemployment, 2005 Annual Averages*. https://www.bls.gov/news.release/archives/srgune_03012006.pdf

Bureau of Labor Statistics. (2008). *Regional and State Unemployment, 2007 Annual Averages*. https://www.bls.gov/news.release/archives/srgune_02292008.pdf

Bureau of Labor Statistics. (2010). *Regional and State Unemployment—2009 Annual Averages*. https://www.bls.gov/news.release/archives/srgune_03032010.pdf

Bureau of Labor Statistics. (2012). *Regional and State Unemployment—2011 Annual Averages*. https://www.bls.gov/news.release/archives/srgune_02292012.pdf

Bureau of Labor Statistics. (2014). *Regional and State Unemployment—2015 Annual Averages*. https://www.bls.gov/news.release/archives/srgune_02262016.pdf

Bureau of Labor Statistics. (2018). *Regional and State Unemployment—2017 Annual Averages*. https://www.bls.gov/news.release/archives/srgune_02272018.pdf

Centers for Disease Control and Prevention. (n.d.). *CDC WONDER*. Retrieved April 5, 2024, from https://wonder.cdc.gov/

Centers for Disease Control and Prevention. (2023a, January 23). *Overdose Deaths and the Involvement of Illicit Drugs | Feature Topics | Drug Overdose*. Centers for Disease Control and Prevention. https://www.cdc.gov/drugoverdose/featured-topics/VS-overdose-deaths-illicit-drugs.html

Centers for Disease Control and Prevention. (2023b, August 8). *Understanding the Opioid Overdose Epidemic | Opioids*. https://www.cdc.gov/opioids/basics/epidemic.html

Centers for Disease Control and Prevention. (2023c, August 25). *The Tax Burden on Tobacco, 1970-2019 | Data | Centers for Disease Control and Prevention*. Centers for Disease Control and Prevention. https://chronicdata.cdc.gov/Policy/The-Tax-Burden-on-Tobacco-1970-2019/7nwe-3aj9/about_data

Centers for Disease Control and Prevention. (2024, April 4). *Fentanyl Facts*. https://www.cdc.gov/stopoverdose/fentanyl/index.html

Centers for Disease Control and Prevention & National Center for Injury Prevention and Control. (2024, February 22). *What You Should Know About Xylazine | Drug Overdose | CDC Injury Center*. https://www.cdc.gov/drugoverdose/deaths/other-drugs/xylazine/faq.html

Ciccarone, D. (2021). The Rise of Illicit Fentanyls, Stimulants and the Fourth Wave of the Opioid Overdose Crisis. *Current Opinion in Psychiatry*, *34*(4), 344–350. https://doi.org/10.1097/YCO.0000000000000717

Doleac, J. L., & Mukherjee, A. (2022). The Effects of Naloxone Access Laws on Opioid Abuse, Mortality, and Crime. *The Journal of Law and Economics*, *65*(2), 211–238. https://doi.org/10.1086/719588

Erfanian, E., Grossman, D., & Collins, A. R. (2019). The impact of naloxone access laws on opioid overdose deaths in the US. *Review of Regional Studies*, *49*(1), 45–72.

Evans, W. N., Lieber, E. M., & Power, P. (2019). How the reformulation of OxyContin ignited the heroin epidemic. *Review of Economics and Statistics*, *101*(1), 1–15.

Federal Reserve Bank of Minneapolis. (n.d.). *Consumer Price Index, 1913- | Federal Reserve Bank of Minneapolis*. Federal Reserve Bank of Minneapolis. Retrieved February 23, 2024, from https://www.minneapolisfed.org/about-us/monetary-policy/inflation-calculator/consumer-price-index-1913-

FRED. (n.d.-a). *2012, Educational Attainment, Annual: Bachelor's Degree or Higher by State | FRED | St. Louis Fed*. FRED Economic Data | St. Louis Fed. Retrieved February 23, 2024, from https://fred.stlouisfed.org/release/tables?rid=330&eid=391444&od=2012-01-01

FRED. (n.d.-b). *Bachelor's Degree or Higher for Alabama | FRED | St. Louis Fed*. FRED Economic Data | St. Louis Fed. Retrieved February 23, 2024, from https://fred.stlouisfed.org/graph/?id=GCT1502AL,GCT1502AK,GCT1502GA,GCT1502HI,GCT1502ID,GCT1502IL,GCT1502IN,GCT1502IA,GCT1502KS,GCT1502KY,GCT1502LA,GCT1502ME,GCT1502AZ,GCT1502MD,GCT1502MA,GCT1502MI,GCT1502MN,GCT1502MS,GCT1502MO,GCT1502MT,GCT1502NE,GCT1502NV,GCT1502NH,GCT1502AR,GCT1502NJ,GCT1502NM,GCT1502NY,GCT1502NC,GCT1502ND,GCT1502OH,GCT1502OK,GCT1502OR,GCT1502PA,GCT1502RI,GCT1502CA,GCT1502SC,GCT1502SD,GCT1502TN,GCT1502TX,GCT1502UT,GCT1502VT,GCT1502VA,GCT1502WA,GCT1502WV,GCT1502WI,GCT1502CO,GCT1502WY,GCT1502CT,GCT1502DE,GCT1502DC,GCT1502FL,

Hamilton, L., Davis, C. S., Kravitz-Wirtz, N., Ponicki, W., & Cerdá, M. (2021). Good Samaritan laws and overdose mortality in the United States in the fentanyl era. *International Journal of Drug Policy*, *97*, 103294.

Kim, B. (2021). Must-access prescription drug monitoring programs and the opioid overdose epidemic: The unintended consequences. *Journal of Health Economics*, *75*, 102408.

Lieberman, A., & Davis, C. (2023a, July 17). *Legal Interventions to Reduce Overdose Mortality: Overdose Good Samaritan Laws*. Network for Public Health Law. https://www.networkforphl.org/resources/legal-interventions-to-reduce-overdose-mortality-overdose-good-samaritan-laws/

Lieberman, A., & Davis, C. (2023b, November 1). *Legal Interventions to Reduce Overdose Mortality: Naloxone Access Laws*. Network for Public Health Law. https://www.networkforphl.org/resources/legal-interventions-to-reduce-overdose-mortality-naloxone-access-and-good-samaritan-laws/

Marijuana Policy Project. (2021, May 28). *Medical Cannabis Program Implementation Timelines*. Marijuana Policy Project. https://www.mpp.org/issues/medical-marijuana/state-by-state-medical-marijuana-laws/medical-marijuana-program-implementation-timeline/

National Conference of State Legislatures. (2022, February 2). *State Medical Cannabis Laws*. https://www.ncsl.org/health/state-medical-cannabis-laws

O'Brien, S. A., & Wernau, J. (2023, January 18). Fentanyl Test Strips on the Dance Floor? Partygoers Face New Reality. *Wall Street Journal (Online)*. https://www.wsj.com/articles/fentanyl-test-strips-party-culture-bars-restaurants-testing-11673993170

Official Missouri State Website. (n.d.). *Governor Parson Signs SB 63: Creating Statewide Prescription Drug Monitoring Program in Missouri | Governor Michael L. Parson*. Official Missouri State Website. Retrieved April 5, 2024, from https://governor.mo.gov/press-releases/archive/governor-parson-signs-sb-63-creating-statewide-prescription-drug-monitoring

Peltzman, S. (1975). The effects of automobile safety regulation. *Journal of Political Economy*, *83*(4), 677–725.

Powell, D., & Pacula, R. L. (2021). The evolving consequences of oxycontin reformulation on drug overdoses. *American Journal of Health Economics*, *7*(1), 41–67.

Powell, D., Pacula, R. L., & Taylor, E. (2020). How increasing medical access to opioids contributes to the opioid epidemic: Evidence from Medicare Part D. *Journal of Health Economics*, *71*, 102286.

Prescription Drug Abuse Policy System. (2016, July 1). *PDMP Reporting and Authorized Use*. Prescription Drug Abuse Policy System. https://pdaps.org/datasets/prescription-monitoring-program-laws-1408223416-1502818373

Prescription Drug Abuse Policy System. (2017a, January). *Medical Marijuana Laws for Patients*. https://pdaps.org/datasets/medical-marijuana-patient-related-laws-1501600783

Prescription Drug Abuse Policy System. (2017b, June 1). *PDMP Implementation Dates*. Prescription Drug Abuse Policy System. https://pdaps.org/datasets/pdmp-implementation-dates

Prescription Drug Abuse Policy System. (2019, January 1). *Drug Induced Homicide Laws*. Prescription Drug Abuse Policy System. https://pdaps.org/datasets/drug-induced-homicide-1529945480-1549313265-1559075032

Prescription Drug Abuse Policy System. (2022a, January 1). *Naloxone Overdose Prevention Laws*. Prescription Drug Abuse Policy System. https://pdaps.org/datasets/laws-regulating-administration-of-naloxone-1501695139

Prescription Drug Abuse Policy System. (2022b). *Good Samaritan Overdose Prevention Laws and Drug Induced Homicide: Summary of State Laws*. https://pdaps.org/datasets/good-samaritan-overdose-laws-1501695153

Prescription Drug Abuse Policy System. (2023, January 1). *Good Samaritan Overdose Prevention Laws*. https://pdaps.org/datasets/good-samaritan-overdose-laws-1501695153

Rees, D. I., Sabia, J. J., Argys, L. M., Dave, D., & Latshaw, J. (2019). With a little help from my friends: The effects of Good Samaritan and naloxone access laws on opioid-related deaths. *The Journal of Law and Economics*, *62*(1), 1–27.

Regional and State Unemployment—2013 Annual Averages. (n.d.). https://www.bls.gov/news.release/archives/srgune_02282014.pdf

Rudd, R. A. (2016). Increases in drug and opioid-involved overdose deaths—United States, 2010–2015. *MMWR. Morbidity and Mortality Weekly Report*, *65*.

Seal, K. H., Downing, M., Kral, A. H., Singleton-Banks, S., Hammond, J.-P., Lorvick, J., Ciccarone, D., & Edlin, B. R. (2003). Attitudes about prescribing take-home naloxone to injection drug users for the management of heroin overdose: A survey of street-recruited injectors in the San Francisco Bay Area. *Journal of Urban Health*, *80*, 291–301.

Tabatabai, M., Cooper, R. L., Wilus, D. M., Edgerton, R. D., Ramesh, A., MacMaster, S. A., Patel, P. N., & Singh, K. P. (2023). The Effect of Naloxone Access Laws on Fatal Synthetic Opioid Overdose Fatality Rates. *Journal of Primary Care & Community Health*, *14*, 21501319221147246. https://doi.org/10.1177/21501319221147246

Tax Policy Center. (2023, February 3). *State Alcohol Excise Tax Rates*. Tax Policy Center. https://www.taxpolicycenter.org/statistics/state-alcohol-excise-tax-rates

The Action Lab. (2024). *Drug Induced Homicide as a Response to Overdose | Health in Justice Action Lab*. The Action Lab. https://www.healthinjustice.org/drug-induced-homicide

This American Life. (2023, August 30). *The Call*. This American Life. https://www.thisamericanlife.org/809/the-call

US Census Bureau. (n.d.-a). *Index of /programs-surveys/popest/tables/2000-2010/intercensal/state*. Census.Gov. Retrieved February 23, 2024, from https://www2.census.gov/programs-surveys/popest/tables/2000-2010/intercensal/state/

US Census Bureau. (n.d.-b). *Index of /programs-surveys/popest/tables/2010-2020/state/totals*. Census.Gov. Retrieved February 23, 2024, from https://www2.census.gov/programs-surveys/popest/tables/2010-2020/state/totals/

US Census Bureau. (n.d.-c). *Index of /programs-surveys/popest/tables/2020-2022/state/totals*. Census.Gov. Retrieved February 23, 2024, from https://www2.census.gov/programs-surveys/popest/tables/2020-2022/state/totals/

US Census Bureau. (n.d.-d). *State and County Intercensal Tables: 1990-2000*. Retrieved February 23, 2024, from https://www.census.gov/data/tables/time-series/demo/popest/intercensal-1990-2000-state-and-county-totals.html

US Census Bureau. (2023, April 21). *Educational Attainment Tables*. Census.Gov. https://www.census.gov/topics/education/educational-attainment/data/tables.html

U.S. Department of Labor. (2024, January). *Changes in Basic Minimum Wages in Non-Farm Employment Under State Law: Selected Years 1968 to 2023*. DOL. http://www.dol.gov/agencies/whd/state/minimum-wage/history

Wooldridge, J. M. (2010). Econometric analysis of cross section and panel data. MIT press.

APPENDIX

Some differences exist with updated data to that of Rees et al. (2019). The variable with the least amount of correlation is PDMPs. However, using updated data or Rees's variables with my data did not notably change the results of any replications. In replicating these regressions, I was able to analyze the effects of GSLs, DIH laws, and NALs, various specifications of these laws, and their interactions, across various timespans. Importantly, I extended the models to include the years 2015-2019. This is especially important as synthetic opioids became the leading driver of ever-increasing opioid overdose mortalities.

Rees et al. seem to use the presence of any naloxone access law enactment date as their data for the naloxone dummy variable except in the case of New York. New York first had enacted a NAL on April 1, 2006. Yet, Rees et al. use the date June 24, 2014, which was when a more specified law was enacted. It includes a change from an earlier enacted February 2007. This change allowed for prescriptions of naloxone to be authorized to third parties. On June 24, 2014, other changes included provisions that allowed pharmacists to dispense or distribute naloxone without a patient-specific prescription from another medical professional, a standing order dispensing method, layperson immunity from criminal liability when administering naloxone, and layperson immunity from civil liability when administering naloxone. It does seem that none of these provisions' presence or absence was a rule used by Rees for selecting other law enactment dates. For instance, Maine has an original enactment date of April 29th, 2014. Yet, there is no civil or criminal immunity for layperson administration of naloxone. Both protections are enacted July 29th, 2016, but Rees et al. use the earlier date. In fact, the only protection specified from the early May 2014 enactment date is that prescriptions of naloxone are authorized to third parties. So, there doesn't appear to be any concrete and consistent rule that determines New York's enactment be the later 2014 law. Yet, with the vagueness of New York's 2006 law contrasted to the greater protections of the 2014 law, it is justified that Rees et al. select June 24, 2014 as the initial date of a NAL in New York (PDAPS, 2022).

Correlations of variables used for replication Tables A2 and A3 are shown in Table A1.

Table A1

Updated Data Correlation with Rees Data

Variables	Correlation
Opioid Deaths	0.999
Ln(Opioid Mortality Rate)	0.998
NAL	1.000
GSL	0.992
Ln(Population)	1.000
PDMP	0.776
Ln(Police Per Capita)	0.932
MML	0.997
Ln(Beer Tax)	0.983
Ln(Cigarette Tax)	0.988
Ln(College Graduates)	0.949
Ln(Per Capita Income)	0.994
Ln(Unemployment Rate)	0.995
Ln(Minimum Wage)	0.973

Table A2 reports the OLS estimates of Equation (1) using Rees's data, my data, and my data with an updated specification of GSL with the addition of a DIH law variable. For the replications, Table A2 and A3, fractions were used to calculate the number of days in which a law was enacted as a percentage of the days of the year. This applies to NALs, GSLs, DIH laws, PDMPs, and MMLs.

Table A2

OLS Replication with Updated Data, 1999-2014

	Rees Baseline	Feir Baseline	Rees	Feir	Updated GSL and DIH
NAL	-0.166**	-0.170**	-0.240***	-0.253***	-0.232***
	(0.067)	(0.065)	(0.077)	(0.080)	(0.082)
GSL	-0.146	-0.140	-0.158*	-0.133	-0.130
	(0.094)	(0.092)	(0.086)	(0.092)	(0.094)
DIH					0.196**
					(0.091)
PDMP			0.045	0.056	0.036
			(0.063)	(0.066)	(0.066)
MML			0.769*	0.558	0.580
			(0.425)	(0.420)	(0.419)
Ln(Police Per Capita)			0.045	0.029	-0.022
			(0.092)	(0.079)	(0.072)
Ln(Beer Tax)			0.233**	0.088	0.067
			(0.091)	(0.115)	(0.110)
Ln(Cigarette Tax)			0.024	0.032	0.036
			(0.056)	(0.054)	(0.054)
Ln(College Graduates)			-0.662	-0.302	-0.307
			(0.581)	(0.201)	(0.196)
Ln(Per Capita Income)			-1.046	-0.399	-0.176
			(0.931)	(0.878)	(0.900)
Ln(Unemployment Rate)			0.089	0.168	0.160
			(0.175)	(0.179)	(0.176)
Ln(Minimum Wage)			-0.634**	-0.853***	-0.884***
			(0.262)	(0.228)	(0.241)
Ln(Population)	-2.676***	-2.627***	-3.324***	-2.946***	-2.867***
	(0.725)	(0.719)	(0.588)	(0.645)	(0.689)
Constant	40.995***	40.323***	61.222***	49.898***	46.421***
	(11.055)	(10.959)	(15.786)	(15.179)	(16.039)
Observations	816	816	816	816	816
R-squared	0.816	0.811	0.832	0.825	0.828

Clustered standard errors in parentheses

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

All OLS coefficients for NAL have substantial magnitude, are significant, and consistently negative. The significance of GSL diminished with updated data. With the adjustment of GSL to include all GSLs rather than the specification of Rees et al., and with the inclusion of DIH, the coefficient of DIH is substantial in magnitude, statistically significant, and positive.

Table A3, a replication of the Poisson, reveals more moderate effects of NAL from 1999-2014, statistical significance for GSL with updated data, and a similar coefficient for DIH, but with only 10 percent significance. Both of these tables show clear decreases for NALs given this timespan, low results of significance for GSLs, and consistent results for DIH laws.

Table A3

Poisson Replication with Updated Data, 1999-2014

	Rees Baseline	Feir Baseline	Rees	Feir	Updated GSL and DIH
NAL	-0.108*	-0.115**	-0.095**	-0.118***	-0.099**
	(0.058)	(0.057)	(0.039)	(0.040)	(0.041)
GSL	-0.136	-0.137	-0.138	-0.158*	-0.163*
	(0.109)	(0.107)	(0.089)	(0.088)	(0.089)
DIH					0.174*
					(0.096)
PDMP			-0.069*	-0.085	-0.100*
			(0.041)	(0.056)	(0.056)
MML			0.536**	0.257	0.256
			(0.226)	(0.232)	(0.230)
Ln(Police Per Capita)			0.078	0.072	0.032
			(0.091)	(0.089)	(0.079)
Ln(Beer Tax)			0.155**	0.086	0.067
			(0.075)	(0.067)	(0.066)
Ln(Cigarette Tax)			0.053	0.065	0.069
			(0.054)	(0.055)	(0.054)
Ln(College Graduates)			-0.356	-0.193	-0.194
			(0.683)	(0.167)	(0.162)
Ln(Per Capita Income)			-0.737	-0.423	-0.213
			(1.174)	(1.145)	(1.186)
Ln(Unemployment Rate)			0.054	0.088	0.096
			(0.202)	(0.223)	(0.222)
Ln(Minimum Wage)			-0.070	-0.480**	-0.485**
			(0.259)	(0.202)	(0.210)
Ln(Population)	-2.387***	-2.248***	-2.555***	-2.074**	-2.025**
	(0.695)	(0.689)	(0.849)	(0.849)	(0.887)
Constant	40.728***	38.666***	50.101**	40.815*	37.888*
	(10.602)	(10.495)	(21.377)	(21.323)	(22.536)
Observations	816	816	816	816	816

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

Table A4

Correlation Matrix

	Ln(Opioid Mortality Rate)	Opioid Deaths	NAL	GSL	DIH	PDMP
Ln(Opioid Mortality Rate)	1					
Opioid Deaths	0.450	1				
NAL	0.505	0.412	1			
GSL	0.489	0.394	0.793	1		
DIH	0.326	0.081	0.231	0.231	1	
PDMP	0.395	0.133	0.420	0.370	0.200	1
MML	0.400	0.206	0.376	0.422	0.235	0.210
Ln(Police Per Capita)	-0.004	0.075	-0.047	-0.029	-0.072	-0.276
Ln(Beer Tax)	-0.17	-0.088	-0.034	-0.007	-0.232	0.032
Ln(Cigarette Tax)	0.411	0.221	0.295	0.317	0.258	0.155
Ln(College Graduates)	0.349	0.236	0.361	0.361	0.102	-0.011
Ln(Per Capita Income)	0.347	0.272	0.349	0.359	0.133	-0.002
Ln(Unemployment Rate)	0.140	0.089	-0.198	-0.159	0.008	0.000
Ln(Minimum Wage)	0.343	0.248	0.362	0.354	0.174	0.125
Ln(Population)	0.050	0.661	0.085	0.066	-0.098	-0.064
GSL with Bystander and Victim Protections	0.479	0.393	0.762	0.962	0.228	0.344
GSL with Controlled Substance Protections	0.466	0.405	0.786	0.933	0.267	0.356
GSL with Paraphernalia Protections	0.330	0.310	0.610	0.716	0.215	0.251
GSL with Parole or Probation Protections	0.325	0.214	0.505	0.579	0.308	0.245
GSL with Mitigating Circumstances Provisions	0.370	0.233	0.522	0.700	0.185	0.227
GSL with no DIH	0.306	0.310	0.572	0.768	-0.207	0.273
GSL with Bystander and Victim Protections and no DIH	0.298	0.310	0.549	0.738	-0.199	0.251
GSL with Bystander and Victim Protections and no DIH or Parole or Probation Protections	0.259	0.267	0.422	0.607	-0.163	0.160

Table A4

Correlation Matrix (continued)

	MML	Ln(Police Per Capita)	Ln(Beer Tax)	Ln(Cigarette Tax)	Ln(College Graduates)	Ln(Per Capita Income)
MML	1					
Ln(Police Per Capita)	-0.179	1				
Ln(Beer Tax)	-0.026	-0.130	1			
Ln(Cigarette Tax)	0.504	0.033	-0.165	1		
Ln(College Graduates)	0.368	0.267	-0.200	0.486	1	
Ln(Per Capita Income)	0.320	0.356	-0.316	0.523	0.803	1
Ln(Unemployment Rate)	0.068	0.072	-0.003	0.117	-0.096	-0.120
Ln(Minimum Wage)	0.534	0.009	-0.109	0.483	0.493	0.492
Ln(Population)	-0.113	0.078	0.025	-0.043	0.015	0.003
GSL with Bystander and Victim Protections	0.449	-0.024	-0.007	0.317	0.377	0.372
GSL with Controlled Substance Protections	0.439	0.016	-0.027	0.307	0.328	0.332
GSL with Paraphernalia Protections	0.271	0.074	-0.098	0.199	0.300	0.297
GSL with Parole or Probation Protections	0.284	0.050	-0.057	0.189	0.229	0.204
GSL with Mitigating Circumstances Provisions	0.352	-0.035	0.041	0.348	0.284	0.276
GSL with no DIH	0.247	-0.068	0.066	0.180	0.238	0.226
GSL with Bystander and Victim Protections and no DIH	0.274	-0.062	0.057	0.189	0.256	0.242
GSL with Bystander and Victim Protections and no DIH or Parole or Probation Protections	0.222	-0.058	0.058	0.189	0.235	0.246

Table A4

Correlation Matrix (continued)

	Ln(Un-employment Rate)	Ln(Minimum Wage)	Ln(Population)	GSL with Bystander and Victim Protections	GSL with Controlled Substance Protections	GSL with Paraphernalia Protections
Ln(Unemployment Rate)	1					
Ln(Minimum Wage)	0.187	1				
Ln(Population)	0.216	-0.026	1			
GSL with Bystander and Victim Protections	-0.145	0.377	0.054	1		
GSL with Controlled Substance Protections	-0.150	0.375	0.076	0.900	1	
GSL with Paraphernalia Protections	-0.152	0.237	0.089	0.661	0.767	1
GSL with Parole or Probation Protections	-0.175	0.233	-0.034	0.602	0.605	0.598
GSL with Mitigating Circumstances Provisions	-0.060	0.343	-0.029	0.688	0.610	0.314
GSL with no DIH	-0.088	0.229	0.096	0.732	0.661	0.497
GSL with Bystander and Victim Protections and no DIH	-0.076	0.250	0.086	0.768	0.638	0.454
GSL with Bystander and Victim Protections and no DIH or Parole or Probation Protections	0.002	0.197	0.089	0.631	0.487	0.275

Table A4

Correlation Matrix (continued)

	GSL with Parole or Probation Protections	GSL with Mitigating Circumstances Provisions	GSL with no DIH	GSL with Bystander and Victim Protections and no DIH	GSL with Bystander and Victim Protections and no DIH or Parole or Probation Protections
GSL with Parole or Probation Protections	1				
GSL with Mitigating Circumstances Provisions	0.382	1			
GSL with no DIH	0.258	0.513	1		
GSL with Bystander and Victim Protections and no DIH	0.275	0.492	0.961	1	
GSL with Bystander and Victim Protections and no DIH or Parole or Probation Protections	-0.111	0.482	0.790	0.821	1

Table A5 reports the OLS and Poisson coefficients of lead and lag variables, as an event study with logged population as the only covariate of each dummy regression.

Table A5

Leads and Lags of GSLs, NALs, and DIH Laws

	GSL OLS	GSL Poisson	DIH OLS	DIH Poisson	NAL OLS	NAL Poisson
3 Years before	-0.049	-0.038	0.011	0.041	-0.069*	0.053
	(0.033)	(0.039)	(0.072)	(0.096)	(0.039)	(0.058)
2 Years before	-0.084*	-0.070	0.111	0.187	-0.069	0.083
	(0.049)	(0.049)	(0.093)	(0.137)	(0.044)	(0.053)
1 Year before	-0.077	-0.056	0.130	0.241	-0.051	0.135**
	(0.072)	(0.073)	(0.107)	(0.152)	(0.056)	(0.063)
Year 0	-0.069	-0.018	0.118	0.243	-0.063	0.169**
	(0.087)	(0.084)	(0.115)	(0.150)	(0.070)	(0.085)
1 Year after	-0.076	-0.075	0.107	0.281*	-0.025	0.263**
	(0.116)	(0.132)	(0.131)	(0.161)	(0.091)	(0.112)
2 Years after	-0.101	-0.144	0.185	0.329*	-0.027	0.300***
	(0.140)	(0.175)	(0.148)	(0.199)	(0.085)	(0.110)
3+ Years after	-0.129	-0.187	0.309*	0.490**	-0.216**	0.153*
	(0.209)	(0.272)	(0.166)	(0.202)	(0.103)	(0.093)
Constant	58.481***	54.734***	55.875***	52.571***	58.520***	53.276***
	(10.36)	(15.91)	(9.687)	(12.58)	(9.573)	(12.57)
Observations	1,071	1,071	1,071	1,071	1,071	1,071
R-squared	0.836		0.840		0.838	

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

This reveals that there is some concern of reverse causality for NALs as there is 5 percent significance and a positive coefficient for one lead with a Poisson regression. Should there be reverse causality, the strict exogeneity assumption is violated for both the OLS and Poisson regressions. However, this would mean that the positive coefficients for mid- and late adopting states are in question, but not the early adopting as such a correlation would raise coefficients.

Table A6 includes the results of a Granger causality test, in which the righthand side variable was number of individuals under a given law regressed against a logged opioid overdose mortality rate, provides additional evidence that there is concern for reverse causality for NALs. It provides some evidence of reverse causality for GSLs as well. There is no evidence for reverse causality for DIH laws. Given these concerns, the sign of the coefficients and economic intuition helps interpret whether reverse causality poses an issue. Firstly, it does pose an issue in assuming NALs have led to increases in opioid overdose mortalities in recent years. It also poses an issue in assuming that mid- and late-adopting states have increased opioid overdose mortalities by passing NALs. Since opioid overdose deaths cause a greater number of people to live under a NAL, it seems legislators have responded to surges in deaths by passing NALs. Yet, more individuals living under a NAL do not significantly cause change for opioid overdose rates according to the Granger causality test. Table A6 indicates they do. As a result, the positive coefficient from mid- and late-adopting states may, in part, signify reverse causality, that NALs were passed in response to surging opioid overdose deaths in those states. I therefore conclude that early-adopting states have decreased opioid overdose rates and am unsure of the effect of mid- and late-adopting states in decreasing opioid overdose rates.

Reverse causality doesn't pose a problem for the interpretation of GSLs or DIH laws. Since GSLs without a DIH present, or interacted with a DIH, have a negative coefficient, it indicates that these laws reduce opioid overdose mortalities. If that were not the case, I would need to assume lawmakers are responding to lower rates of overdoses with the passage of these laws. Over time, rates have only increased, along with the passage of these laws, so I conclude that the passage of laws are reducing rates in those states in comparison to other states without such laws. If there is reverse causality present for GSLs, that would indicate that their effect in reducing opioid-related deaths is greater than was found by my models. DIH laws do seem to increase opioid overdose rates as there is only 10 percent significance for granger causality with two lags that overdose rates cause DIH laws. Yet, there is 1 percent significance for all lags that DIH laws cause opioid overdose rates. Since these coefficients are consistently positive and statistically significant, I assume that DIH laws increase opioid overdose deaths. Therefore, I have further confidence that these laws do diminish the ability of GSLs to reduce opioid overdose deaths.

Table A6

Granger Causality

Question and Lags	Answer	Significance
Do GSLs cause deaths?		
1 lag	No	
2 lags	No	
3 lags	No	
4 lags	No	
Do deaths cause GSLs?		
1 lag	Yes	1%
2 lags	Yes	5%
3 lags	Yes	5%
4 lags	Yes	1%
Do DIH laws cause deaths?		
1 lag	Yes	1%
2 lags	Yes	5%
3 lags	Yes	1%
4 lags	Yes	5%
Do deaths cause DIH laws?		
1 lag	No	
2 lags	No	
3 lags	No	
4 lags	No	
Do NALs cause deaths?		
1 lag	No	
2 lags	No	
3 lags	No	
4 lags	No	
Do deaths cause NALs?		
1 lag	Yes	1%
2 lags	Yes	1%
3 lags	Yes	1%
4 lags	Yes	5%

Figure A1

Event Study Analysis of GSLs on Opioid-Related Deaths

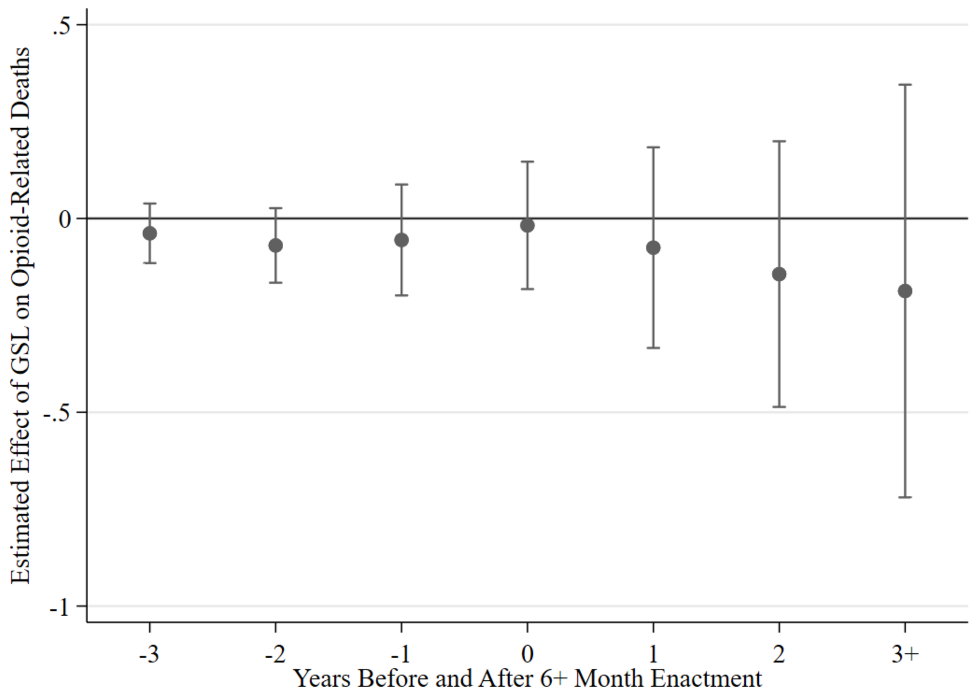


Figure A2

Event Study Analysis of DIH Laws on Opioid-Related Deaths

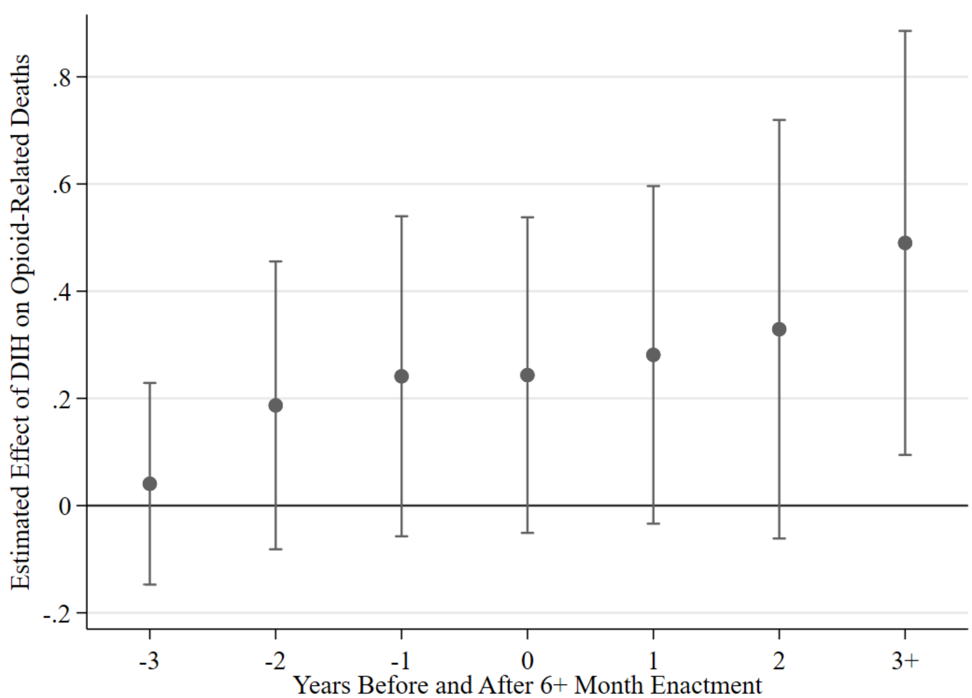
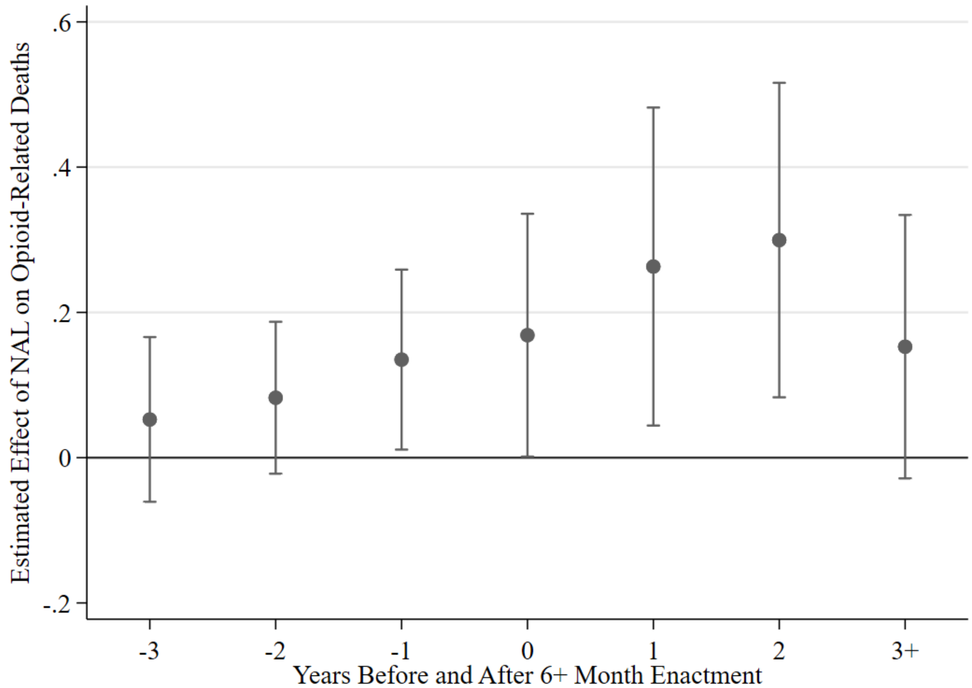


Figure A3

Event Study Analysis of NALs on Opioid-Related Deaths



Appendix Tables A7, A8, and A9 correspond to Tables 5, 6, and 7, which are my main results relating to GSLs and their relationship with DIHs. In the appendix tables, NALs were excluded. This was because there is concern of endogeneity among NALs and GSLs. Yet, aside from GSL becoming slightly insignificant in Appendix Table A8, there is little difference when excluding NALs. This mitigates concern for their endogeneity for the tables included in the paper.

Table A7

Heterogeneity of GSLs Excluding NALs

	OLS	Poisson
GSL × Caller and Victim Protection	-0.241	-0.210
	(0.155)	(0.133)
GSL × Controlled Substance Possessions	0.063	0.023
	(0.125)	(0.141)
GSL × Paraphernalia Possessions	0.055	0.022
	(0.109)	(0.070)
GSL × Parole or Probation Protections	0.167	0.257***
	(0.109)	(0.067)
GSL × Mitigating Factors	0.046	0.072
	(0.110)	(0.066)
DIH	0.080	0.053
	(0.076)	(0.050)
Constant	65.608***	64.638***
	(13.539)	(18.001)
Observations	1,071	1,071
R-squared	0.853	

Clustered standard errors in parentheses

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

Table A8

Interaction of GSLs and DIH Laws Excluding NALs

	Standard GSL		GSL with Victim and Bystander Protection	
	OLS	Poisson		OLS
DIH	0.063	-0.033	0.025	-0.063
	(0.099)	(0.010)	(0.110)	(0.107)
GSL	-0.072	-0.103	-0.125	-0.127
	(0.086)	(0.086)	(0.088)	(0.079)
GSL × DIH	0.047	0.024	0.019	0.010
	(0.119)	(0.113)	(0.126)	(0.110)
Constant	69.854***	69.016***	69.300***	68.431***
	(15.391)	(20.354)	(14.483)	(19.324)
Observations	1,071	1,071	1,071	1,071
R-squared	0.849		0.850	

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

Table A9

Effective GSLs Excluding NALs

	OLS	Poisson	OLS	Poisson	OLS	Poisson
GSLs with no DIH Law	-0.090	-0.115**				
(N = 177)	(0.066)	(0.051)				
… and Caller and Victim Protections			-0.132*	-0.132***		
			(0.066)	(0.048)		
(N = 165)						
… and without Parole or Probation Protections					-0.175**	-0.190***
					(0.076)	(0.060)
(N = 115)						
Observations	1,071	1,071	1,071	1,071	1,071	1,071
R-squared	0.849		0.850		0.852	

Clustered standard errors in parentheses

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

Table A10

Interaction of NALs and DIH Laws

	OLS	Poisson
GSL	-0.051	-0.089
	(0.088)	(0.082)
DIH	0.086	0.022
	(0.103)	(0.098)
NAL	-0.051	0.056
	(0.052)	(0.051)
NAL × DIH	0.047	0.175***
	(0.101)	(0.059)
Constant	70.301***	67.733***
	(15.602)	(20.556)
Observations	1,071	1,071
R-squared	0.849	

Clustered standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$