2019

Should States Adopt Overdose Immunity Laws?

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JORDAN NORTON

35 Pages

From 2014-2015, the CDC saw a 72.2% increase in death rates related to synthetic opioids other than methadone, and a 20.6% increase in heroin related death rates. States have looked to one another for policy examples that would bring these numbers down. One of the earliest of these policies came out of 2001 in New Mexico with the first Naloxone Access Laws (NALs) followed by Drug Overdose Immunity Laws (DOILs) in 2007. These laws sought to remove barriers to people administering Naloxone and calling emergency responders due to overdoses, granting immunity to callers and overdose sufferers. This study looked at data from 799 counties over the period of 2006-2016 and used a Pooled OLS multivariate regression model to determine the effects of the breadth of protections provided by the DOILs, NALs, inequality and income in the counties, and categories of race/ethnicity and educational attainment. The biggest effect on death rates was seen in inequality, followed by presence of NALs and breadth of DOIL protection. Yearly regressions showed decreasing death rates according to laws overtime with a slight increase due to late adoption of DOILs. Some variables remain difficult to control for, and though the study has shown mixed results, the policy is a good tool in a multipronged attack on the opioid epidemic.

KEYWORDS: opioids, drug related mortality, drug policy, law enforcement

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A Thesis Submitted in Partial
Fulfillment of the Requirements
for the Degree of

MASTER OF SCIENCE

Department of Politics and Government

ILLINOIS STATE UNIVERSITY

2019

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ACKNOWLEDGMENTS

A huge thanks to my colleagues, my partner, my family, and my friends who have supported me through the program and helped me figure out this research stuff. I would especially like to thank my committee members for the time they have dedicated towards helping me become successful in my graduate studies.

J.N.

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CHAPTER I: OPIOID EPIDEMIC AND OVERDOSE IMMUNITY POLICIES

"Persons in the United States consume opioid pain relievers (OPR) at a greater rate than any other nation. They consume twice as much per capita as the second ranking nation, Canada" (Palouzzi, Mack, Hockenberry, 2014 pp. 125). The United States currently faces a public health crisis of epidemic proportions. Mainly, this has been the result of the increased prescription of opioids among physicians. Starting from a high point of 72.4 opioid prescription per 100 persons in 2006 and growing by 4.1 percent annually to 2008 when the rate decreased to a 1.1 percent annual increase into 2012. After the peak in 2012, the rate has begun to decrease by 4.9 percent each year (CDC, 2017). Even with this decreased prescription, drug death rates have continued to climb. Drug death rates from synthetic opioids other than methadone have increased by 72.6% from 2014-2015; for heroin, the rates have increased by 20.6% in the same time period (Rudd, et al., 2016).

While the decreased rate of opioid prescription has been positive, reducing the number of persons introduced to the substance and subsequently becoming addicted, the damage has been done. Today, about 80 percent of heroin users report the misuse of prescription opioids prior to using heroin (HHS, 2018). Not everyone who abuses prescription painkillers will go on to use heroin, but a large enough number will. Different states face different levels of opioid prescription, and therefore, abuse and addiction. A map of the different levels of prescriptions as of 2012 can be seen in Appendix A.

The problem of prescription medications goes beyond merely drug abuse but begins to touch on how communities and governments can deal with a rise in drug overdoses and drug-related deaths within those communities. This epidemic of deaths and the need for emergency services has been taxing for communities across the country as they struggle with ever decreasing budgets while attempting to maintain high levels of service. The work of individuals is crucial in this realm, as seen in a recent Netflix documentary *Heroin(e).* This film shows the lives of three women attempting to work on this epidemic in Huntington, West Virginia, a town with an overdose rate ten times the national average (McMillon & Sheldon, 2017).

Throughout the rise of this public health epidemic, governments have been primarily relying on traditional punitive measures stemming from the War on Drugs to combat the issue. From 1980-2015, the number of federal prisoners incarcerated for drug-related offenses went from 5,000 to 92,000, making up nearly half of the federal prison population as of 2015. Similarly, between 1980 and 2013, spending on federal prisons increased 595% (Pew Charitable Trusts, 2015). While the overall incarceration rate as of 2016 has decreased to its lowest levels since 1993, the federal numbers say that the punitive philosophy related to drug use isn't going anywhere (Kaeble & Cowhig, 2018). The big question with these punitive measures is, do they work? A 2017 Pew analysis of those in prison for drug-related offenses found no relation between drug-related imprisonment and a state's drug problems. In other words, they saw that drug sentencing did not work to deter drug users (Pew Charitable Trusts, 2017).

This is not just an issue among states, but also among localities. Even as California boasts one of the lowest overdose rates in the country, Humboldt County, a rural northern county has seen its drug-related death rates rise to five times greater than the state average (Del Real, 2018). Fragmentation among municipalities at the local level, among states, and the federal government has slowed progress in tackling this issue. This has been especially slowed in the face of budget cuts at every level of government and a lack of coordination between the federal, state and local governments. In many cases, localities have worked to take on the issues, being careful not to step on the toes of their state. Syringe and needle exchange programs have popped up around the country; though primarily serving more urban populations, these programs hope to stop the spread of diseases such as HIV and Hepatitis C. Opioid replacement therapies in many have also shown their ability to ween individuals off high doses towards independence from the drugs. Cities are also calling for the introduction of Supervised Injection Sites in their locales, with planned sites in Seattle and new talk of sites in Minneapolis. While cities and counties have been quick to act as the vanguard in this battle, the state and federal governments have been slower to experiment.

Recently, though, there has been a shift in political will to tackle the issue. The opiate crisis has been the primary public health priority thus far for the Trump administration, as seen when, in 2017, the acting director of the Department of Health and Human Services declared the opioid crisis a public health emergency (DHHS, 2017). Since then, the Trump Administration has requested an increase in the National Drug Control Budget through the Office of National Drug Control Policy (ONDCP) from $27.5 billion in Fiscal Year 2017 to $27.8 billion for Fiscal Year 2018 (ONDCP, 2017). The budget included key incentives for treatment, as well as state grants targeted at opioid addiction treatment.

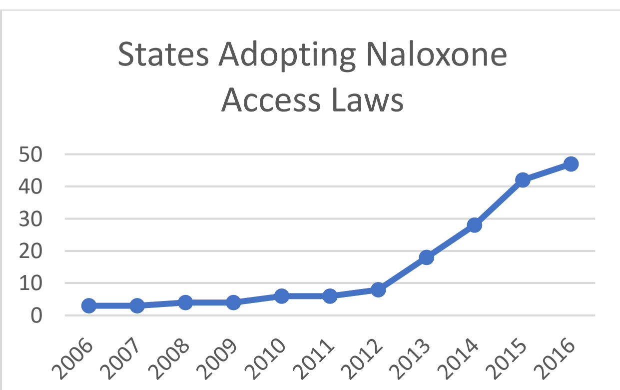
Thus far, the Department of Health and Human Services (DHHS) has developed a five-point strategy in the hopes of tackling the issue. It includes "(1) Better Addiction Prevention, Treatment and Recovery Services (2) Better Data (3) Better Pain Management (4) Better Targeting of Overdose Reversing Drugs (5) Better Research" (DHHS 2018). These five targeted areas show the willingness of the federal government to tackle the issue with a variety of evidence-based tools. Increasing cooperation among federal agencies and state/local governments will be a key to this process. Allowing states and localities to implement novel policies will be part of the solution.

Naloxone and Overdose Immunity Laws

Large doses of opioids are problematic as they act on a portion of the brain that is also responsible for breathing. When an individual has taken too much of the drug, they may experience pinpoint pupil dilation, unconsciousness, and reduction in respiration (WHO, 2018). Naloxone, an overdose rescue drug, works as an antagonist drug, specifically to opioids. When it is given to a person overdosing on opioids, the opioids acting on the person will be blocked from affecting the person as the receptors are effectively taken up by the Naloxone. This will help to restore consciousness and increase respiration, although the person will still need to be referred to emergency services (NIDA, 2018).

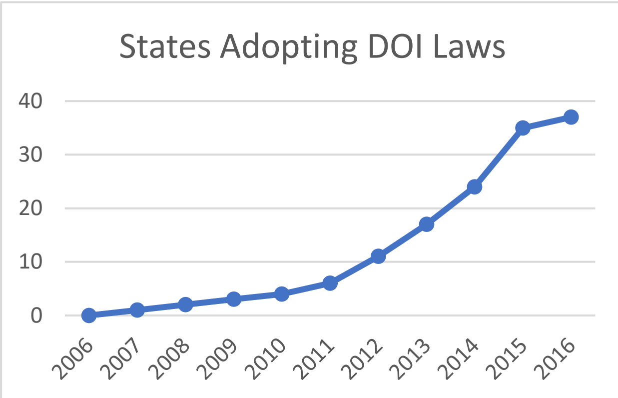
First approved in the United States for use in the case of an opioid overdose in 1971, Naloxone is currently available in several forms. In its injectable form, administering it generally requires training from professionals. It is also available in an auto injectable form like Epinephrine auto injectables in the EpiPen, and in a nasal spray form requiring no injection. Community and family/friends of addicts may purchase the auto injectable or nasal spray in many states through Naloxone Access Laws. These laws provide legal protection for prescribers and to laypersons whom may be administering the drug onsite before the arrival of first responders.

Figure 1: States Adopting Naloxone Access Laws



The first Naloxone Access Laws (NALs) were passed in 2001 by New Mexico and many states were slow to follow. This was followed in 2007, with the first adoption of a set of laws called Drug Overdose Immunity Laws (DOILs), also known as Good Samaritan

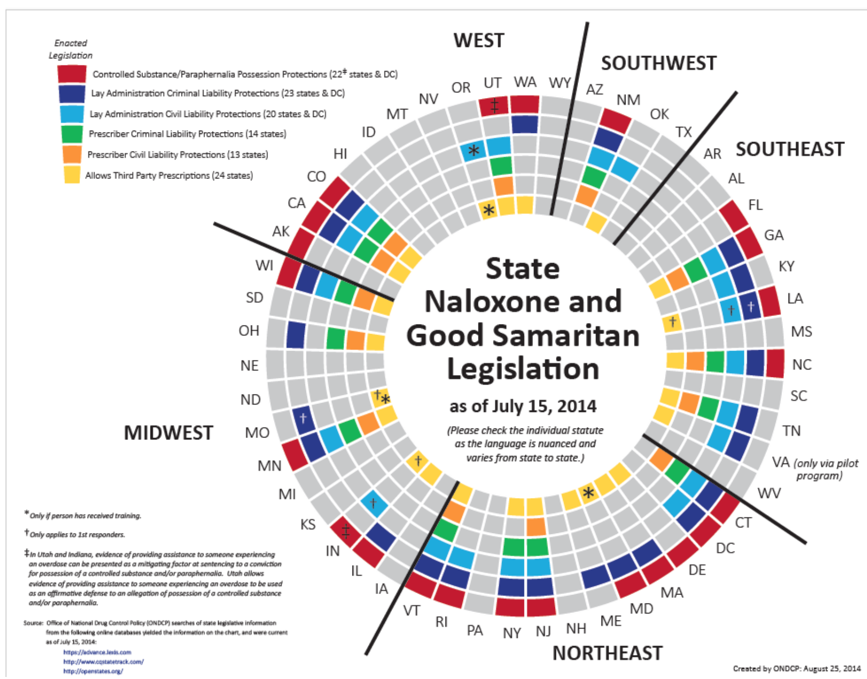
Figure 2: States Adopting Drug Overdose Immunity Laws



Laws. Other states were slow to follow with both NALs and DOILs. In some cases, states would adopt NALs before subsequent adoption of DOILs years later, but in many cases both policies were adopted in the same year, particularly as the issue became more prominent in the public's eye. The adoption trend of both laws from 2006-2016 can be seen in the charts to the left, and is represented in map form in Appendix C. At present, 45 states and Washington, D.C. have adopted some sort of DOILs and all 50 states and Washington, D.C. have allowed for access to Naloxone through NALs (PDAPS 2018).

The legal protections granted under the laws vary from state to state. An ONDCP chart from 2014, seen to the right, shows the range of protections afforded by different states. Here we see that, as of 2014, twenty-two states and Washington, DC provide protections for those in possession of controlled substances or paraphernalia thereof and say that

Figure 3: State Naloxone and Good Samaritan Legislation (2014)



only trained individuals may give the treatment of Naloxone. Twenty-three states and Washington DC allow lay persons to provide Naloxone and provide for protection from criminal prosecution. Twenty states and DC allow lay Naloxone use and protection from civil litigation. Fourteen states provide criminal protection to Naloxone prescribers, while thirteen provide civil protection. Twenty-four of the states allowed for third party prescriptions, where the Naloxone is given to someone other than the drug user who could potentially be administering the drug to the person (ONDCP, 2014).

Public Health Advocates

NALs and DOILs have been heralded by different organizations as effective. In a 2014 resolution, the United States Conference of Mayors declared their support for the policies across the United States (USCM, 2014). The Network for Public Health Law described the Drug Overdose and Naloxone Laws as the “low hanging fruit” in public health law, as there were no foreseeable negative effects to offset the possibility of saving lives through overdose intervention (NPHL, 2016).

Studies have so far acknowledged that the largest barrier to individuals in calling emergency responders is the fear of police (Baca & Grant, 2007; Pollini, et al., 2006). They have also shown that those most likely to witness an overdose were less likely to contact first responders, and that younger individuals were also less likely to call and wait (Follet, 2012). Laws in place may not necessarily be common knowledge though. As first responders learn more about the laws, they’re ability to handle the situation in a legal fashion and therefore intervene, has a higher chance of success (Banta-Green, et al., 2013). One study found that overdoses occurring where a witness had been trained and educated on the New York State Good Samaritan laws, bystanders were three times more likely to call 911 than in instances where individuals had incorrect knowledge of Good Samaritan Laws (Jakubowski, et al. 2017). While research shows a promising policy, education is key to making the policy work. As localities often have differences of opinion in how to distribute public health education dollars, it is important to investigate the efficacy of the policies as they take effect.

The Data

The study done here hoped to analyze the efficacy of these policies, with specific regard to DOILs as they have not yet become universal law among the states. Utilizing the Center's for Disease Control's (CDC) Wide-ranging Online Data for Epidemiologic Research (WONDER) database, raw drug overdose deaths and populations by county were gathered for the years 2006-2016. This resulted in 9,073 individual observations covering 1, 257 counties. The number of drug overdose deaths were divided by county populations, then multiplied by 100,000 giving a death rate per 100,000 population allowing the study to directly compare the death rates by county (CDC 2019). While this measure does not account for only opioid related deaths, the National Institute on Drug Abuse (NIDA) has shown that opioids are a primary driver of drug overdose deaths in the recent past and any decrease in opioid related deaths would show up as a reduction in drug overdose deaths (NIDA 2019).

From the Prescription Drug Abuse Policy System's (PDAPS) interactive map of "Good Samaritan Overdose Prevention Laws" was gathered the data of state law levels of protection extended to individuals in possession of controlled substances from 2006-2016 (PDAPS 2018). The existence of the NALs at the level of the state from 2006-2016 was gathered from PDAPS's interactive "Naloxone Overdose Prevention Laws" map (PDAPS 2017).

Variables including gini index numbers, median income, and measures of educational attainment and race/ethnicity were gathered from the United States Census Bureau's American

Factfinder (USCB 2019). When combining all variables, only those county/year observations that had data for each variable were kept. The CDC's overdose death count was unfortunately incomplete each year, eliminating many observations. Data collection and reporting did improve each year with a greater number of counties being reported, though the pattern was random. Drug related death data has become a priority for CDC in recent years and they are working to improve their systems of collection (CDCOPHSS 2019). In any case, this resulted in a final count of 7,336 observations over 799 counties.

Research Methodology

This study used ordinary least squares (OLS) regression models as well as Poisson regression models with both fixed and random effects through the STATA 15 software program. It sought to determine the relationship between drug overdose death rates in counties and the extent of protections provided by state DOILs along with several other variables over the period of 2006-2016. A general pooled regression first looked at differences in death rates based on the variables among all observations. Next, a pooled regression was conducted for counties within each year to determine whether there were differences in the coefficient trends among the variables from year to year and to track the effect of the variables over time. Unfortunately, these pooled regressions treat all the observations as a homogenous mixture while there is quite a diversity of thought and culture among the different states that may affect levels of drug use in the communities. Because of this, the study finally sought to utilize fixed and random effects models to control for differences among states and counties. Both fixed and random effects models were run controlling for state and counties. After this a Hausman test was run to determine which model should be used. For state-controlled effects, a random effects model was determined to be the best. For county-controlled effects, a fixed effects model was determined to be the best. Finally, a county-controlled fixed effects model was run with a lagged dependent variable (death rate) that included the effect of time.[1]

The Variables

This study looks to determine how several variables act upon the death rate. This means that the death rate per 100,000 for each county will be used as the dependent variable. The primary independent variable addresses how differences in the laws among the states may influence the death rate. It is titled Law Level and is a coded representation of a state's adoption or nonadoption of the policy and the breadth of protections it extends to those in possession of controlled substance. As these individuals are the more likely to witness an overdose and yet the least likely to contact emergency services due to the barriers described previously, it is these individuals that can make the most difference and whom are targeted by the protections in these laws. The state laws were coded from 0-4. In the analysis, a county in a state with no DOILs is coded as a 0. If a state has laws, but no protections for those individuals, it is coded as a 1. Above this, a county will have a higher code number dependent on the number of protections provided up to a 4. These protections may include protection from arrest, charge, or prosecution, or the law may provide an affirmative defense or other procedural protections. There were 3 cases in which stipulations were put on the protections; these have been coded 0.5 less than their regular code. This includes Indiana, where it is up to the officer on scene to determine if the individual took steps to save the overdosing person, Ohio, where an individual may not be granted immunity more than two times, and Tennessee, where the immunity only applies to a

[1] After analyzing the results of the fixed and random effects models, it was determined that the resulting coefficients did not significantly differ from those among the pooled regressions. These tables were therefore not included in the main body or analysis. They can, however, be found in Appendix E.

person experiencing their first overdose (PDAPS 2018). A list of state laws and the protections they provide under DOILs is in a table in Appendix B.

The existence of NALs in state law was also utilized as an independent variable. These laws were the first to start addressing the issue of opioids in communities and brought about the subsequent adoption of DOILs. NALs were coded with a simple binary of 0 or 1, where 0 was a county in a state without the NALs and 1 was a county in a state with NALs. This inclusion is important as a recent study of the same issue utilizing state level data found that states with NALs and DOILs were associated with 14% and 15% reductions in opioid overdose deaths respectively (McClellan, et al. 2018).

Looking at the laws alone cannot tell researchers whether it is just the laws having an effect or if there are other factors at play in the equation. In this case, some other independent variables will need to be added to the model to get a better understanding of what is happening in each community. An additional broad measure allowing us to investigate individual communities is the use of the Gini Index for each county in each year. This statistical tool is used to measure income distribution and inequality in a given population. It ranges from 0 to 1, where 0 represents perfect equality (i.e. everyone has the same income/wealth) and 1 represents perfect inequality (i.e. one individual has all the income/wealth). This measure has been linked to health outcomes among both countries in the world and states within the U.S. Those populations, shown in the graphs to the right, with a lower Gini index, meaning greater equality, have been shown to higher life expectancy, and communities with higher Gini indexes, greater inequality, see higher rates of schizophrenia (Inequality 2019). As this study is looking at a policy related to public health, this variable helps us to build a more complete picture of this large data set.

Additionally, it was decided to include median income of the counties over the years. While the Gini Index gives us an idea of income distribution among the communities, it does not give us an idea of the actual wealth of the community. A county of lower income people may show up with a high Gini index and wouldn't give us a real complete picture of the community that may have a high death rate, but that won't be associated with poverty, but rather equality and throw off our data.

Figure 4: Chart of Variables

Dependent Variable	Independent Variables
Overdose Death Rate	Levels of Protection
	Naloxone Access Laws
	GINI Index
	Median Income
	Percent Population with High School Diploma
	Percent Population with Bachelor's or more
	Percent Population Identified as White
	Percent Population Identified as Black
	Percent Population Identified as Latino

Another measure will be education; in this case looking at county percentages of those with a high school degree and percentages with a bachelor's or higher. Studies have shown an association between drug use and level of education; therefore, it is important to include this variable as well **(**Bachman, et al., 2008). Race/ethnicity including percentages of white, black, and Latino residents will also be included as an independent variable. Race/ethnicity has been shown to be of high value as a variable when looking into issues of criminal justice as it's been shown that even with comparable rates of drug use, black men are 3.6 times more likely to be arrested for selling drugs and 2.5 times more likely to be arrested for drug possession than white men (Rothwell 2014). These communities may therefore be less likely than average to contact emergency services.

Hypotheses

H1: In the general pooled regression, increased protections for individuals in possession of controlled substances will decrease drug overdose death rates. DOILs aim to reduce the boundaries individuals may face to call first responders, thereby reducing the overdose death rate due to increased response to overdoses. Given this, the greater protection extended to individuals should work to further encourage those individuals and increase response.

H2: In the yearly pooled regressions, coefficients for death rates will be negative due to the increasing effectiveness of the laws. As DOILs take effect, the knowledge of their protections will take time to spread among individuals. This will cause a decrease in death rates over time and will show up as a trend of decreasing coefficients.

CHAPTER II: POOLED REGRESSIONS

General Pooled Regression

In the general pooled regression, all 7,336 observations were individual treatments independent of one another and treated as a homogenous mixture. It was hypothesized that the increase in protections for individuals in possession of controlled substances would be associated with a decrease in drug overdose death rates. This was due to the thought that the laws act to remove barriers to individuals reporting overdoses and greater protections would provide more encouragement to those individuals to report.

Analysis

The multiple linear regression model yielded significant results listed on the following page in Table 1. The model utilized 7,336 observations and showed an R^2 value of 0.246, meaning that the independent variabless used here explain roughly 25% of the variation in the Overdose Death Rate. While it was hypothesized that the increased protections for those in possession of controlled substances would show a decrease in the death rate, this model revealed a slight increase of 0.735 per 100,000 population with each increase in the level of protection and a death rate 3.02 higher in counties with NALs than in those without. These increases may be due to late adopting states having already high death rates and adopting the laws with greater levels of protection for those in possession.

Table 1: Pooled Regression Results

Pooled Regression

Independent Variable	Death Rate
Levels of Protections	0.735***
	(0.0902)
Naloxone Access Laws	3.019***
	(0.253)
Gini Index	67.76***
	(3.723)
Median Income	0.00000887
	(0.0000107)
Percent Pop with High School Diploma	0.0782*
	(0.0321)
Percent Pop with Bachelor’s or Higher	-0.314***
	(0.0166)
Percent Pop Identified as White	0.0709***
	(0.00993)
Percent Pop Identified as Black	-0.0572***
	(0.0127)
Percent Pop Identified as Latino	-.157***
	(0.0102)
Constant	-16.83***
	(3.459)
N	7336
R-sq	0.245706

Standard errors in parentheses

* p < 0.05, ** p < 0.01, *** p < 0.001

Though law level and NAL adoption was an important part of this model, it was shown that the Gini Index had the largest effect on the death rate, seeing a sizable positive coefficient representing an increase in death rates with a one unit increase in the Gini Index. This represents a steep rise as the minimum death rate in the data set was 1.56/100,000 and the maximum was 106.26/100,000. Interestingly, the related variable of median income was seen to be statistically insignificant.

For high school graduation rates, an increase by one percent represented a growth of 0.0782 in death rate while an increase in percentages of population holding a bachelor's degree or more represented a 0.314 decrease in the death rate. For race/ethnicity, an increase by one percent among the white share of the population represented a growth of 0.0709 growth in the death rate. Increases in black and Latino populations represented a 0.07 and 0.16 drop in the death rate respectively.

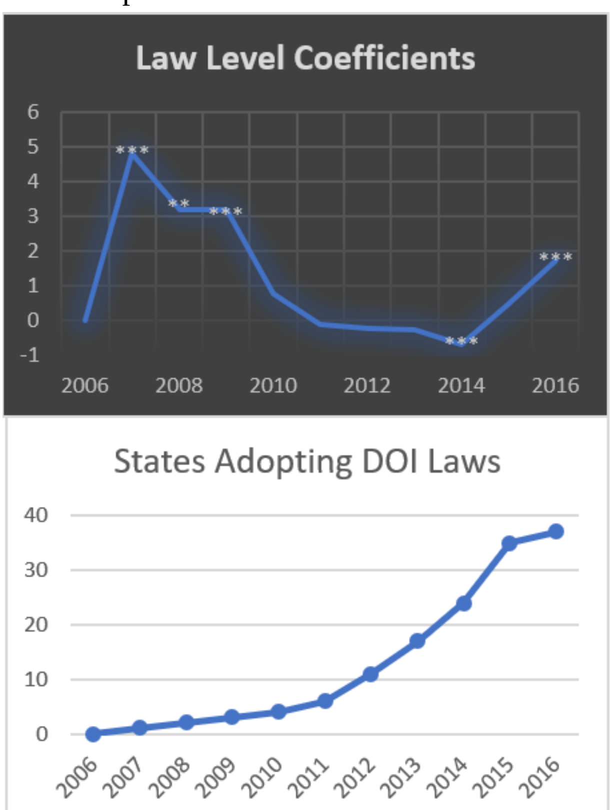
This model revealed some significant results that started to create a picture of how these variables were interacting. While it was hypothesized that increasing protections for individuals in possession of controlled substances, a slight increase in the death rate was noted with this model. This meant that the hypothesis failed to be confirmed, though the coefficient may have had influence from those states that were late adopters with already high rates of overdose deaths. This model did, however, take out a key element of changing interactions over time. The laws may be effective, but they may need time to take effect. The effects of those late adopting states may also be seen more effectively when looking at trends over time. This was the thought behind the group of models presented next.

Yearly Pooled Regressions

The yearly pooled regression treated each year as its own model and compared the results over time. It was hypothesized that the coefficients for death rates based on law level would decrease overtime due to the increasing effectiveness of the laws. As was noted earlier, increased knowledge of the laws among individuals was associated with higher levels of reporting. Thus, as public health education and the knowledge of the laws spreads over time, the barriers to contacting emergency services are reduced and therefore death rates would decrease with the ensuing increased overdose reporting.

Analysis

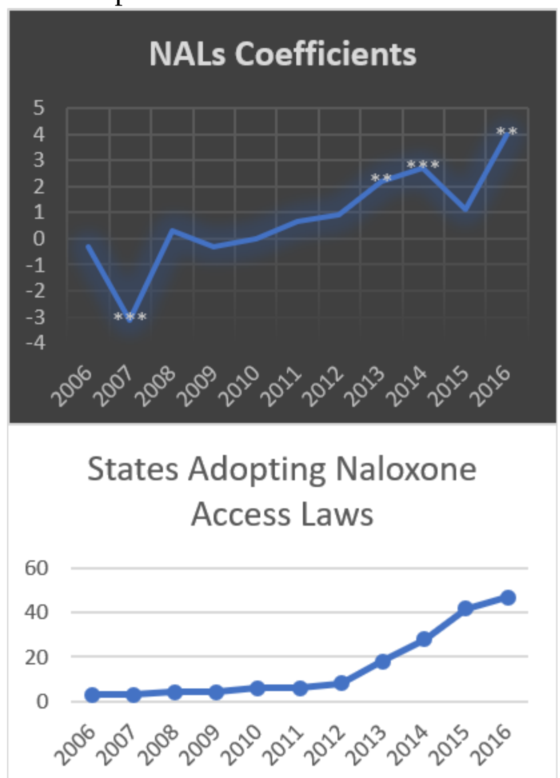
Figure 5: Law Level Coefficients and State Law Adoption



The yearly pooled regression models also revealed some significant results, but they also allowed us to detect trends in the coefficients that were not otherwise visible. The full table of models is available in Appendix C. Looking at the law levels and the trending of it's coefficients, seen in the chart to the left, we do start to see a downward slope starting with the reduction in significant results from 4.82 in 2007 to 3.15 in 2009, meaning a reduction of 1.67 deaths/100,000 with increasing levels of protection. While several years do not provide significant, the year 2014 reveals that the laws did begin to have their intended effect with a coefficient of -0.71 with each increasing level of protection. While it is seen that there is a sharp spike after 2014 up to 1.73 in 2016, we can see in the chart of state DOIL adoption below the chart of coefficients that there was also a sharp spike in the adoption of these laws by states in 2015 and 2016. This may be an effect of late adopting states with already high overdose death rates affecting the coefficient.

A similar trend is seen among the NALs coefficients, seen in the chart to the right. The first NALs were adopted from 2001 onward and by 2006, 3 states had the laws. These laws had had the time to take effect and the first significant coefficient was negative, showing that counties with the laws had 3.14 deaths/100,000 population less than those counties without. The next several of years' worth of coefficients lack significance, though an upward trend is easily seen. The next significance comes at 2.18 in 2013 and finally a 4.01 in 2016. Like the law levels, the upward trend in coefficients matches the adoption of the laws by states seen in the chart to the right. Therefore, that upward trend indicates that states with already high overdose death rates are adopting these policies in an attempt to reduce those deaths having seen the success of early adopters.

Figure 6: NALS Coefficients and State Law Adoption



Another point of interest came from the finding that there were no years in which median income played a significant role in the model based on overdose death rates. However, when looking at the trend in the Gini Index, it was seen that inequality played a large role in each model with a high level of significance to each coefficient. Not only this, but that from 2006 to 2016, the coefficient doubled, indicating a steep rise in death rates among those counties with greater inequity.

Education levels and measures of race/ethnicity played small roles in the models, holding steady over the time frame of the study and having varying levels of significance. But this group of models revealed a whole new dimension of understanding in looking at the trends of the variables over time. The law levels began to show that, when given time to take effect, they were associated with decreasing death rates. Thus the hypothesis was partially, though not fully, confirmed. The trend of decreasing coefficients, along with the first negative coefficient for death rates when measured against law levels gave clues to indicate some effectiveness in the laws. This paired with the increased adoption of both DOILs and NALs by states indicates that policy makers are seeing effectiveness in the laws and hope to bring that same efficacy to their own states. While median income showed no relationship with death rates, inequality (here measured by the Gini Index) showed a relationship indicative of issues beyond the scope of this study, though certainly worthy of study and a useful tool for those hoping to attack the opioid epidemic on a variety of fronts.

CHAPTER III: CONCLUDING REMARKS

The original hypothesis that increased protections for individuals in possession of controlled substances would reduce drug overdose death rates was unable to be fully confirmed. However, numbers indicated that there was some impact happening. When looking at the trends in coefficients on a year to year basis, it was observed that in the year 2014 there began to be a decrease in death rates with increased protections, beyond that effects from later adopting states were seen. Reduced numbers were also seen with the introduction of controls for state and county, and especially for time.

Time is key to the study of this set of policies, as it takes time, and political will, to educate the public on them, and it has been shown before that education is key to breaking down the barriers in reporting an overdose. One of the largest issues in the study is in accounting with the differential spending from community to community on public health education and the number of people that are reached by this education. Further studies would do well to create an index of this spending on a county to county basis and utilize this spending as a variable.

The country is also in a period of flux regarding drug policy and attempts to take on the opioid epidemic. Future studies would be aided by knowledge of prescription rates broken up by individual county. It is also still unclear as to the exact effect of medical and recreational marijuana on opioid overdoses as these policies are still relatively new, little research has been done. One study has shown that, in the case of Colorado, recreational marijuana has had an influence on opioid overdose deaths (Livingston, et al. 2017). Another factor that may be influencing death rates is the rising cost of Naloxone drugs, as a private company that began to produce the brand EVZIO in 2014 has subsequently raised the price of the drug by 600 percent as of 2018 (Alltucker, 2018).

With all this said, several public health and public policy organizations continue to advocate for the protections given by these policies. States have widely adopted them and, though at varying levels, given assurances that will help to break down the barriers to reporting experienced by those that are most likely to witness an overdose event. Though studies are ongoing, states that remain without DOILs will continue without this “low hanging fruit” policy as it was described by the Network for Public Health Law (NPHL), and continue to see the same results.

An important point that has come out of this study is the understanding of the role that inequality may play in predicting overdose deaths rates. As the United States has witnessed a rise in inequality in the recent past (Bachman 2017), it is wise to take these staggering numbers seriously. If the opioid epidemic is to be addressed seriously, the country will need to take on the issue of inequality. The inequality shown in the Gini index may show a disparity of resources that would also benefit from an understanding of the public health education dollars being spent in communities. If this connection is made, states may find that one way to work on the issue is to distribute their public health education funding based on a measurement of inequality in those communities. In any case, the opioid epidemic is a multidimensional issue being worked on from many angles in the micro sense with harm reduction programs and in the macro sense with the rise of lawsuits aimed at pharmaceutical producers of the pain killer drugs. There may be no silver bullet policy, but this is a start.

WORKS CITED

Alltucker, Ken. 2018. "Drug company raised price of lifesaving opioid overdose antidote more than 600 percent". Retrieved from https://www.usatoday.com/story/news/health/2018/11/19/kaleo-opioid-overdose-antidote-naloxone-evzio-rob-portman-medicare-medicaid/2060033002/

Baca, CT, Grant, K. 2007. "What Heroin Users Tell Us About Overdose." *Journal of Addictive Diseases* 26(4): 63-68

Bachman, Jerald G., O'Malley, Patrick M., Schulenburg, John E., Johnston, Lloyd D., Freedman-Doan, Peter, Messersmith, Emily E. 2008. "Substance Use, Ages 14 to 40, Linked to Educational Success" In *The Education-Drug Use Connection.* (pp. 3-10). New York, NY: Taylor & Francis Group, LLC.

Banta-Green, Caleb J., Beletsky, Leo, Schoeppe, Jennifer A., Coffin, Phillip O., Kuszler, Patricia C. 2013. "Police Officers' and Paramedics' Experiences with Overdose and Their Knowledge and Opinions of Washington State's Drug Overdose-Naloxone-Good Samaritan Law" *Journal of Urban Health.* 90(6): 1102-1111.

Carson, E. Ann and Anderson, Elizabeth. 2016. "Prisoners in 2015" Retrieved from https://www.bjs.gov/content/pub/pdf/p15.pdf

Centers for Disease Control (CDC) WONDER. 2018. "Compressed Mortality File" Retrieved from wonder.cdc.gov.

Centers for Disease Control and Prevention (CDC). 2017. "Prescribing Data" Retrieved from https://www.cdc.gov/drugoverdose/data/prescribing.html

Centers for Disease Control and Prevention (CDC). 2017. “Annual Surveillance Report of Drug-Related Risks and Outcomes” Retrieved from https://www.cdc.gov/drugoverdose/pdf/pubs/2017-cdc-drug-surveillance-report.pdf

Center for Disease Control and Prevention, Office of Public Health Scientific Services (CDCOPHSS). 2019. “Modernizing Drug Death Data” Retrieved from https://www.cdc.gov/surveillance/projects/improving-data-on-drug-overdose-deaths.html

Del Real, Jose A. 2018. “Needle by Needle, a Heroin Crisis Grips California’s Rural North” Retrieved from https://www.nytimes.com/2018/05/08/us/california-heroin-opioid.html?smid=fb-nytimes&smtyp=cur

Department of Health and Human Services (DHHS). 2017. “HHS Acting Secretary Declares Public Health Emergency to Address National Opioid Crisis” Retrieved from https://www.hhs.gov/about/news/2017/10/26/hhs-acting-secretary-declares-public-health-emergency-address-national-opioid-crisis.html

Department of Health and Human Services (DHHS). 2018. “The Opioid Epidemic in Numbers” Retrieved from http://www.hhs.gov/opioids/

Department of Health and Human Services (DHHS). 2018. “5-Point Strategy to Combat the Opioid Crisis” Retrieved from https://www.hhs.gov/opioids/about-the-epidemic/hhs-response/index.html

Florida Department of Law Enforcement. 2016. “UCR Arrest Data” Retrieved from http://www.fdle.state.fl.us/FSAC/Data-Statistics/UCR-Arrest-Data.aspx

Follett K. 2012 “Between life and death: The barriers to calling 9-1-1 during an overdose emergency.” Waterloo Region Crime Prevention Council. 1-45.

Harm Reduction International. 2018. “What is Harm Reduction?” Retrieved from https://www.hri.global/what-is-harm-reduction

Inequality.org. 2019. “Inequality and Health” Retrieved from https://inequality.org/facts/inequality-and-health/

Jakubowski, A, Kunins, HV, Huxley-Reicher, Z, Siegler, A. 2017. “Knowledge of 911 Good Samaritan Law and 911-calling behavior of overdose witnesses.” *Substance Abuse.* 39(2): 233-238.

Kaeble, Danielle and Cowhig, Mary. 2018. “Correctional Populations in the United States, 2016” Retrieved from https://www.bjs.gov/content/pub/pdf/cpus16.pdf

Livingston, Melvin D., Barnett, Tracy E., Delcher, Chris, Wagenaar, Alexander C. 2017 “Recreational Cannabis Legalization and Opioid-Related Deaths in Colorado, 2000–2015”, *American Journal of Public Health* 107(11): pp. 1827-1829.

McClellen, C., Lambdin, BH, Ali, MM, Mutter, R, Davis, CS, Wheeler, E., Pemberton, M., Kral, AH. 2018. “Opioid-overdose laws association with opioid use and overdose mortality” *Addictive Behavior* 86: 90-95.

Nadelmann, Ethan and LaSalle, Lindsay. 2017. “Two Steps Forward, One Step Back: Current Harm Reduction Policy and Politics in the United States”. *Harm Reduction Journal* 14(37): 1-7.

National Conference of State Legislatures. 2017. “Drug Overdose Immunity and Good Samaritan Laws” Retrieved from http://www.ncsl.org/research/civil-and-criminal-justice/drug-overdose-immunity-good-samaritan-laws.aspx

National Institute on Drug Abuse (NIDA). 2018. “Opioid Overdose With Naloxone (Narcan, Evzio)” Retrieved from https://www.drugabuse.gov/related-topics/opioid-overdose-reversal-naloxone-narcan-evzio

National Institute on Drug Abuse (NIDA). 2019. “Overdose Death Rates” Retrieved from https://www.drugabuse.gov/related-topics/trends-statistics/overdose-death-rates

Network for Public Health Law (NPHL). 2017. “Legal Interventions to Reduce Overdose Mortality: Naloxone Access and Overdose Good Samaritan Laws” Retrieved from https://www.networkforphl.org/_asset/qz5pvn/network-naloxone-10-4.pdf

Office of National Drug Control Policy (ONDCP). 2017. “National Drug Control Budget: FY 2018 Funding Highlights”. Retrieved from https://www.whitehouse.gov/sites/whitehouse.gov/files/ondcp/Fact_Sheets/FY2018-Budget-Highlights.pdf

Office of National Drug Control Policy (ONDCP). 2014. “State Naloxone and Good Samaritan Legislation” Retrieved from https://obamawhitehouse.archives.gov/sites/default/files/ondcp/Blog/naloxonecirclechart_august2014.pdf

Paulozzi, Leonard J., Mack, Karin A., Hockenberry, Jason M. 2014. “Variation among states in prescribing of opioid pain relievers and benzodiazepines- United States 2012” *Journal of Safety Research* 51:125-129.

Pew Charitable Trusts. 2015. “Federal Prison System Shows Dramatic Long-Term Growth” Retrieved from http://www.pewtrusts.org/en/research-and-analysis/fact-sheets/2015/02/federal-prison-system-shows-dramatic-long-term-growth

Pew Charitable Trusts. 2017. “Pew Analysis Finds No Relationship Between Drug Imprisonment and Drug Problems” Retrieved from http://www.pewtrusts.org/en/research-and-analysis/speeches-and-testimony/2017/06/pew-analysis-finds-no-relationship-between-drug-imprisonment-and-drug-problems

Pollini RA, McCall L, Mehta SH, Celentano DD, Vlahov D, Strathdee SA. 2006. “Response to overdose among injection drug users.” *American Journal of Preventative Medicine* 31(3):261-264.

Prescription Drug Abuse Policy System (PDAPS). 2017. “Naloxone Overdose Prevention Laws” Retrieved from http://pdaps.org/datasets/laws-regulating-administration-of-naloxone-1501695139

Prescription Drug Abuse Policy System (PDAPS). 2018. “Good Samaritan Overdose Prevention Laws”. Retrieved from http://pdaps.org/datasets/good-samaritan-overdose-laws-1501695153

Puzzanchera, C. and Kang, W. 2017. “Easy Access to FBI Arrest Statistics 1994-2014” Retrieved from http://www.ojjdp.gov/ojstatbb/ezaucr/

Rothwell, Johnathan. 2014. “How the War on Drugs Damages Black Social Mobility” Retrieved from https://www.brookings.edu/blog/social-mobility-memos/2014/09/30/how-the-war-on-drugs-damages-black-social-mobility/

Rudd, Rose A., Seth, Puja, David, Felicita, Scholl, Lawrence. 2016. “Increases in Drug and Opioid-Involved Overdose Deaths- United States, 2010-2015” *Morbidity and Mortality Weekly Report* 65(50-51): 1445-1452.

McMillon, Elaine and Sheldon, Kerrin. 2017. *Heroin(e).* United States: Netflix

State of Alabama. 2014. "2014 Alabama Sheriff and Police Department Arrests for Sale/Possession of Illegal Drugs" http://www.alea.gov/Documents/Documents/DrugCrime2014.pdf

State of Illinois. 2014. "Index Crime Offense & Crime Rate Data" https://www.isp.state.il.us/docs/cii/cii14/cii14_sectioni_pg11_to_242.pdf

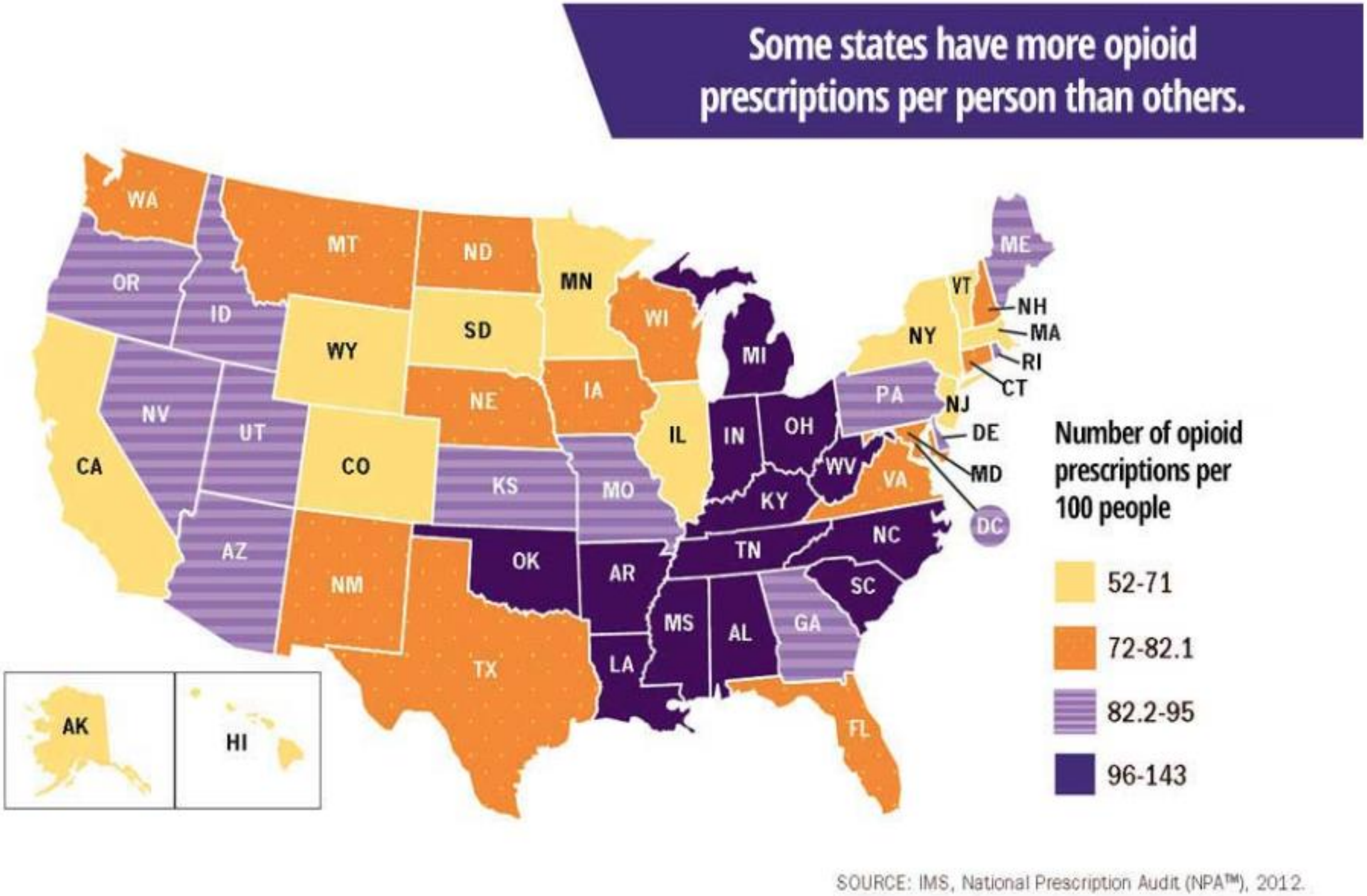
United States Census Bureau (USCB). 2019. 2012-2016 American Community Survey 5-year Estimates; generated by Jordan Norton; using American Fact Finder; <https://factfinder2.census.gov>

United States Conference of Mayors (USCM). 2014. "Resolution: Saving Lives Through Overdose Prevention" Retrieved from https://www.usmayors.org/the-conference/resolutions/?category=d20019&meeting=82nd%20Annual%20Meeting

World Health Organization (WHO). 2018. "Information Sheet on Opioid Overdose" Retrieved from http://www.who.int/substance_abuse/information-sheet/en/

US Department of Health and Human Services. 2018. "The Opioid Epidemic in Numbers" Retrieved from https://www.hhs.gov/opioids/

APPENDIX A: STATE OPIOID PRESCRIPTIONS PER PERSON



APPENDIX B: TABLE OF STATE DRUG OVERDOSE IMMUNITY LAWS

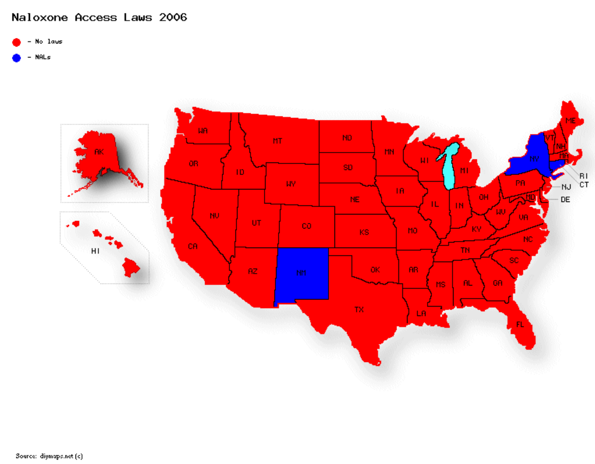
Table B1

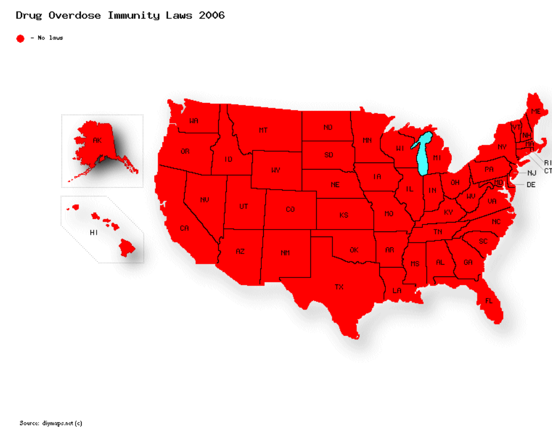
State	Law	Effective Date	None	Arrest	Charge	Prosecution	Affirmative Defense	Note
Alabama	**Ala. Code § 20–2–281**	6/9/2015	-	-	-	Yes	-	
Alaska	**Alaska Stat. § 11.71.030**	7/11/2016	-	-	-	Yes	-	
Arizona	-	-	Yes	-	-	-	-	
Arkansas	**Ark. Code § 20–13–1704**	7/21/2015	-	Yes	Yes	Yes	-	
California	**Cal. Health & Safety Code § 1137**	12/31/2012	-	Yes	Yes	Yes	-	
Colorado	**Colo. Rev. Stat. § 18-1-711**	8/9/2016	-	Yes	-	Yes	-	
Connecticut	**Conn. Gen. Stat. § 21a-279**	9/30/2015	-	Yes	Yes	Yes	-	
Delware	**Del. Code. tit. 16, § 4769**	8/30/2013	-	Yes	Yes	Yes	-	
District of Colombia	**D.C. Code § 7-403**	3/18/2013	-	Yes	Yes	Yes	-	
Florida	**Fla. Stat. § 893.21**	9/30/2012	-	-	Yes	Yes	-	
Georgia	**Ga. Code § 16-13-5**	4/23/2014	-	Yes	Yes	Yes	-	
Hawaii	**Haw. Rev. Stat. § 329-43.6**	7/6/2015	-	Yes	Yes	Yes	-	
Idaho	-	-	Yes	-	-	-	-	
Illinois	**720 Ill. Comp. Stat. 570/414**	5/31/2012	-	-	Yes	Yes	-	
Indiana	**Ind. Code § 35-38-1-7.1**	6/30/2015	-	Yes*	-	Yes	-	* Pursuant to Ind. Code § 16-42-27-2, an officer may not take an individual into custody based solely on the commission of an act subject to the Good Samaritan law if the law officer reasonably believes that the individual undertook certain delineated actions to prevent an overdose.
Iowa	-	-	Yes	-	-	-	-	
Kansas	-	-	Yes	-	-	-	-	
Kentucky	**Ky. Rev. Stat. § 218A.133**	3/24/2015	-	-	Yes	Yes	-	
Louisiana	**La. Rev. Stat. § 14:403.10**	7/31/2014	-	-	Yes	Yes	-	
Maine	-	-	Yes	-	-	-	-	
Maryland	**Md. Code, Crim. Proc. § 1-210**	9/30/2016	-	Yes	Yes	Yes	-	
Massachussets	**Mass. Gen. Laws ch. 94C, § 34A**	8/2/2012	-	-	Yes	Yes	-	
Michigan	-	-	Yes	-	-	-	-	
Minnesota	**Minn. Stat. § 604A.05**	6/30/2014	-	-	Yes	Yes	-	
Mississippi	**Miss. Code § 41-29-149.1**	6/30/2016	-	Yes	Yes	Yes	-	
Missouri	-	-	Yes	-	-	-	-	
Montana	-	-	Yes	-	-	-	-	
Nebraska	-	-	Yes	-	-	-	-	
Nevada	**Nev. Rev. Stat. § 453C.150**	9/30/2015	-	Yes	Yes	Yes	-	
New Hampshire	**N.H. Rev. Stat. § 318-B:28-b**	9/5/2015	-	Yes	-	Yes	-	
New Jersey	**N.J. Stat. § 2C:35-31**	5/1/2013	-	Yes	Yes	Yes	-	
New Mexico	**N.M. Stat. § 30-31-27.1**	6/14/2007	-	-	Yes	Yes	-	

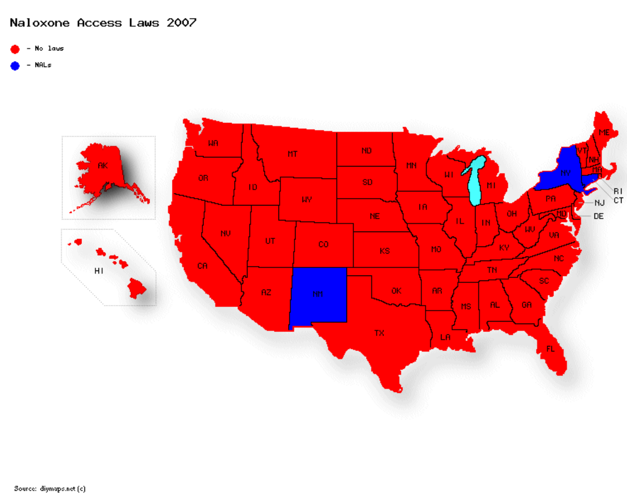
State	Law	Effective Date	What protection, if any, does the law provide from controlled substance posession laws? None	Arrest	Charge	Prosecution	Affirmative Defense	Note
New York	**N.Y. Penal Law § 220.78**	9/17/2011	-	-	Yes	Yes	-	
North Carolina	**N.C. Gen. Stat. § 90-96.2**	7/31/2015	-	-	-	Yes	-	
North Dakota	**N.D. Cent. Code § 19-03.1-23.4**	8/1/2015	-	-	-	Yes	-	
Ohio	**Ohio Rev. Code § 2925.11**	9/13/2016	-	Yes*	Yes	Yes	-	* Pursuant to Ohio Rev. Code § 2925.11(f), an individual may not be granted immunity more than two times.
Oklahoma	-	-	Yes	-	-	-	-	
Oregon	**Or. Rev. Stat. § 475.898**	1/1/2016	-	Yes	-	Yes	-	
Pennsylvania	**35 PA. Cons. Stat. § 780-113.7**	11/30/2014	-	-	Yes	Yes	-	
Rhoda Island	**R.I. Gen. Laws § 21-28.9-4**	1/26/2016	-	-	Yes	Yes	-	
South Carolina	-	-	Yes	-	-	-	-	
South Dakota	-	-	Yes	-	-	-	-	
Tennessee	**Tenn. Code § 63-1-156**	6/30/2015	-	Yes*	Yes	Yes	-	* The immunity from being arrested, charged, or prosecuted in Tenn. Code § 63-1-156 applies to a person experiencing their first drug overdose only.
Texas	-	-	Yes	-	-	-	-	
Utah	**Utah Code § 76-3-203.11**	3/19/2014	-	-	-	-	Yes	
Vermont	**Vt. Stat. tit. 18, § 4254**	6/16/2014	-	Yes	-	Yes	-	
Virginia	**Va. Code § 18.2-251.03**	6/30/2015	-	-	-	-	Yes	
Washington	**Wash. Rev. Code § 69.50.315**	7/23/2015	-	-	Yes	Yes	-	
West Virginia	**W. Va. Code § 16-47-4**	6/11/2015	-	-	-	Yes	-	
Wisconsin	**Wis. Stat. § 961.443**	4/9/2014	-	-	-	Yes	-	
Wyoming	-	-	Yes	-	-	-	-	

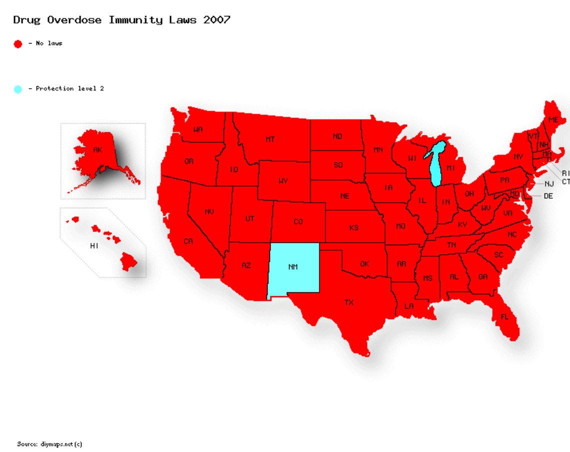
APPENDIX C: STATE NALOXONE ACCESS AND DRUG OVERDOSE IMMUNITY LAWS

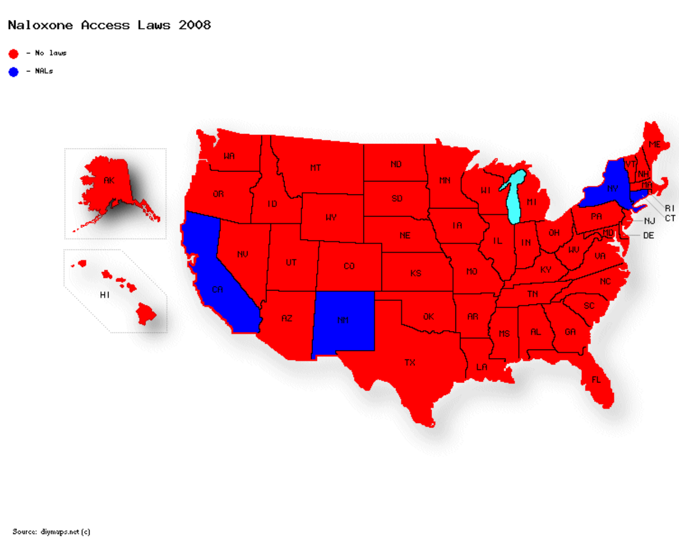
2006-2016

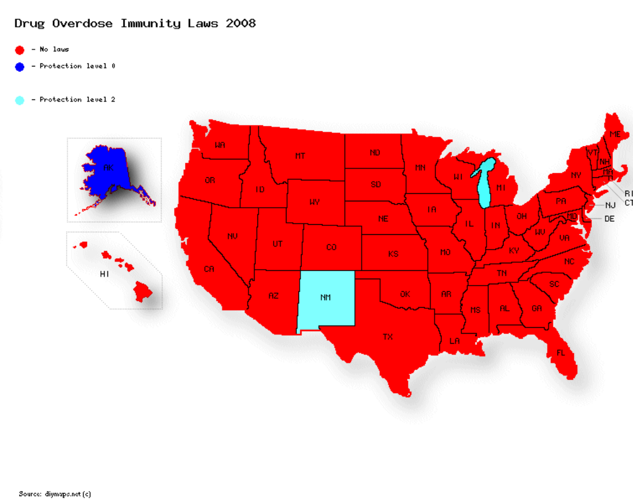












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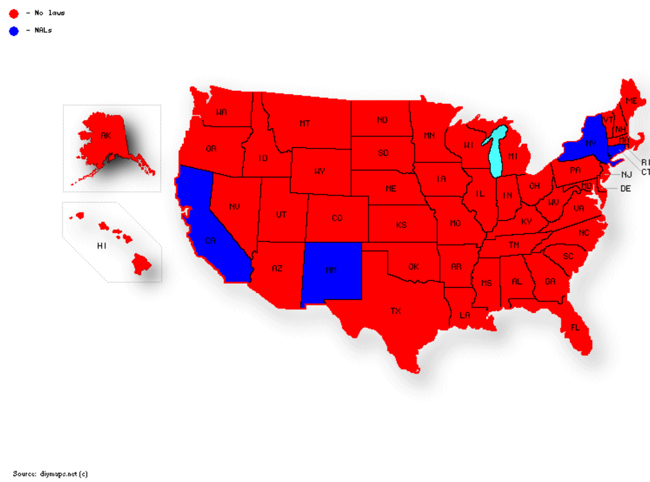

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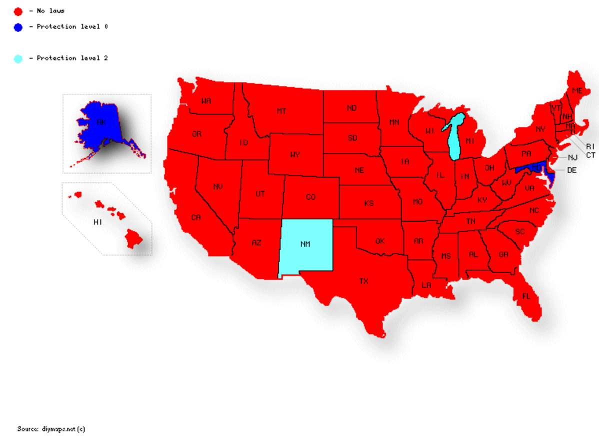

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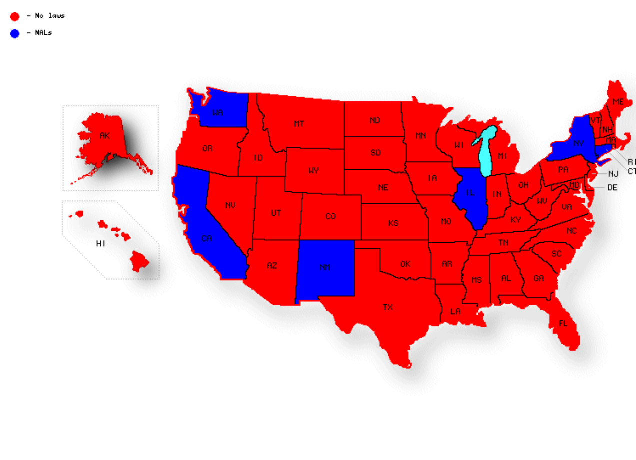

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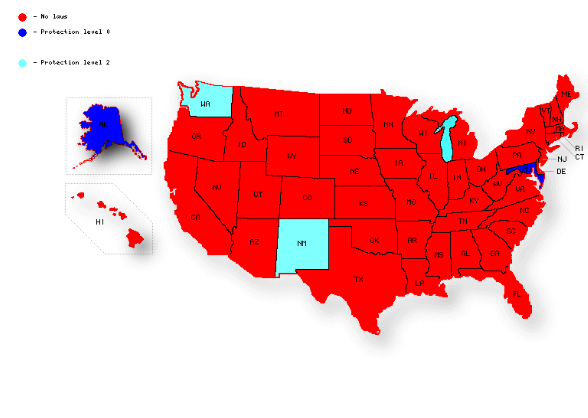

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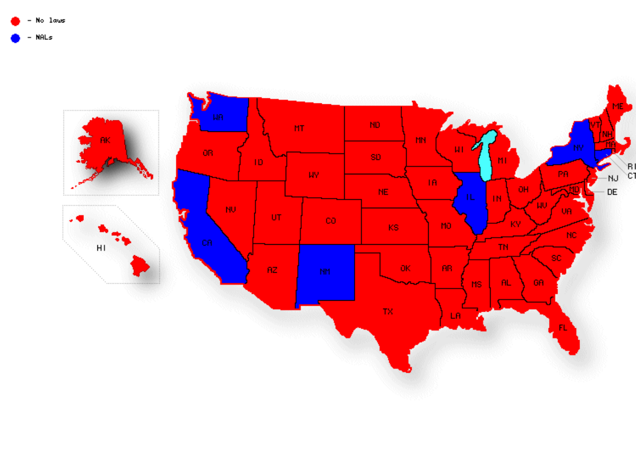

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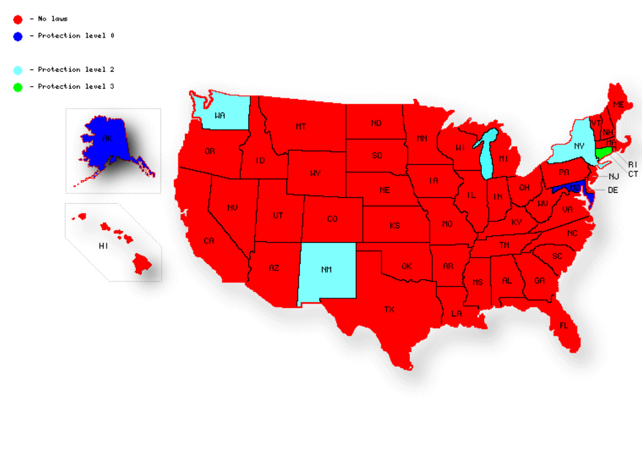

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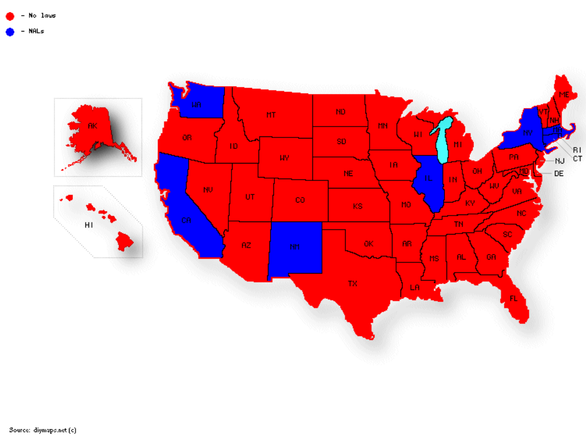

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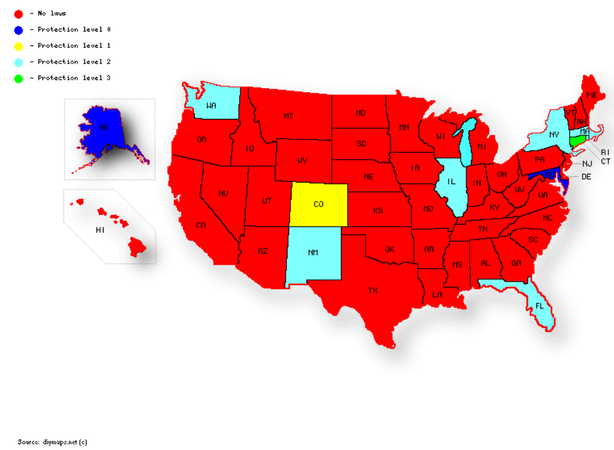

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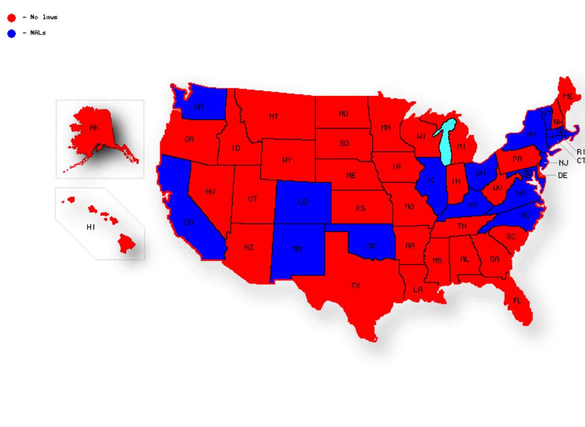

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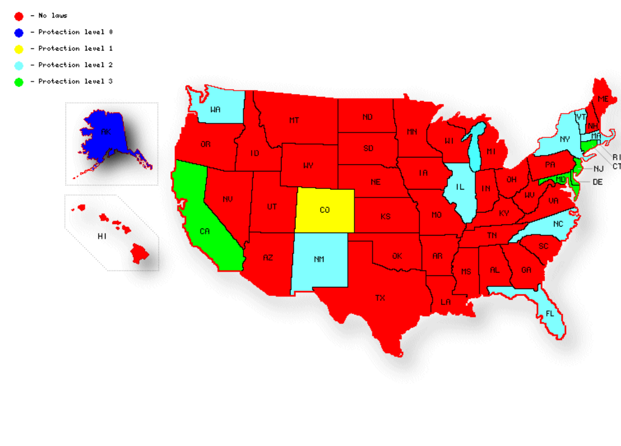

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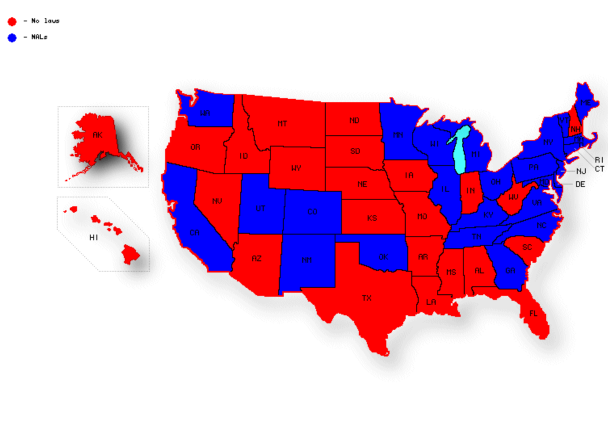

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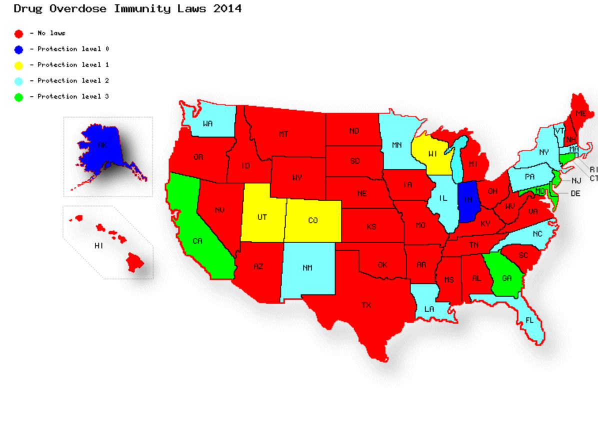
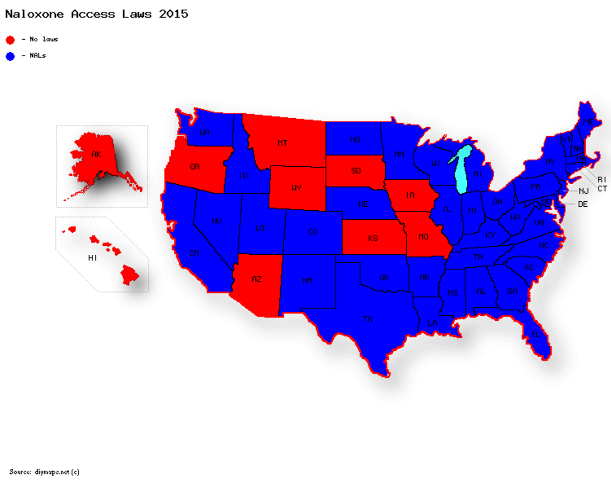
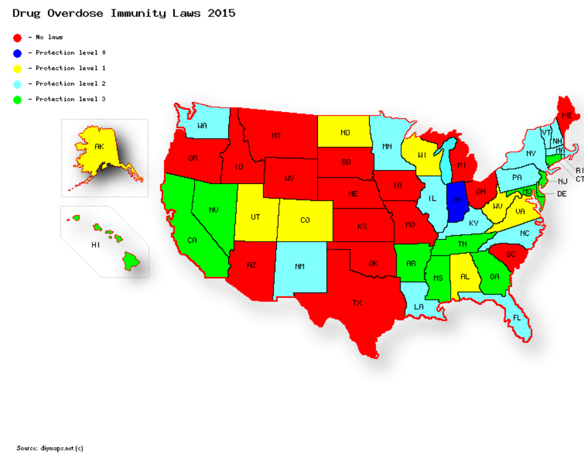
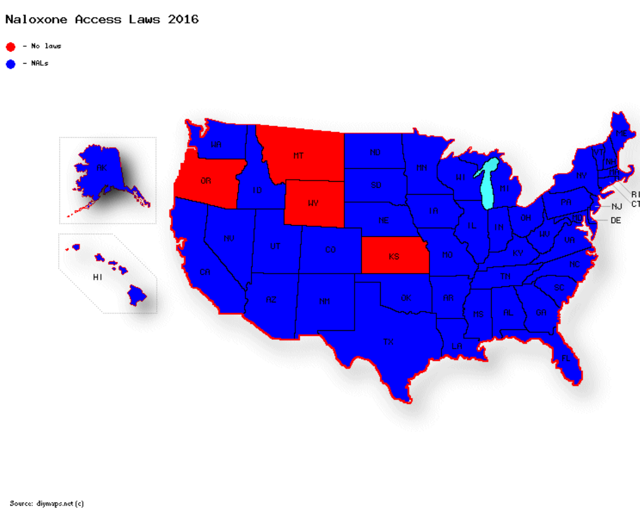
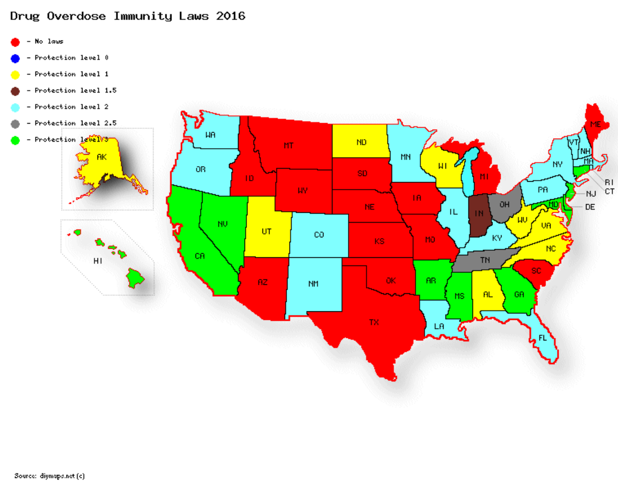



Naloxone Access Laws 2015
- No laws
- NALs
Source: diymaps.net (c)


Drug Overdose Immunity Laws 2015
- No laws
- Protection level 0
- Protection level 1
- Protection level 2
- Protection level 3
Source: diymaps.net (c)


Naloxone Access Laws 2016
- No laws
- NALs
Source: diymaps.net (c)


Drug Overdose Immunity Laws 2016
- No laws
- Protection level 0
- Protection level 1
- Protection level 1.5
- Protection level 2
- Protection level 2.5
- Protection level 3
Source: diymaps.net (c)

APPENDIX D: YEARLY POOLED REGRESSION TABLE

Table D1

Pooled Regression

	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Levels of Protection	0	4.822***	3.198**	3.193***	0.753	-0.137	-0.260	-0.288	-0.705***	0.433	1.725***
	(.)	(1.182)	(1.109)	(0.664)	(0.498)	(0.404)	(0.226)	(0.211)	(0.191)	(0.227)	(0.287)
Naloxone Access Laws	-0.288	-3.143***	0.318	-0.292	0.0145	0.663	0.928	2.180**	2.720***	1.126	4.009**
	(1.073)	(0.705)	(0.856)	(0.904)	(0.880)	(1.044)	(0.777)	(0.686)	(0.665)	(1.129)	(1.368)
Gini Index	50.46***	61.94***	55.98***	40.95***	47.41***	50.63***	47.45***	60.04***	77.13***	75.97***	100.4***
	(9.334)	(9.318)	(8.536)	(9.064)	(9.813)	(9.838)	(9.375)	(11.19)	(12.22)	(15.05)	(18.98)
Median Income	-0.0000176	0.0000163	-0.0000226	-0.0000339	-0.0000188	-0.0000209	0.00000212	0.00000639	0.0000265	0.0000355	0.0000804
	(0.0000360)	(0.0000287)	(0.0000295)	(0.0000280)	(0.0000300)	(0.0000299)	(0.0000271)	(0.0000313)	(0.0000343)	(0.0000360)	(0.0000455)
Percent Pop with High school Dipoma	-0.0688	-0.0703	0.0326	0.0845	-0.137	-0.0733	-0.0493	-0.0625	-0.0514	-0.0785	0.438**
	(0.0851)	(0.0915)	(0.0890)	(0.0876)	(0.125)	(0.142)	(0.108)	(0.0976)	(0.124)	(0.125)	(0.135)
Percent Pop with Bachelor's or Higher	-0.220***	-0.230***	-0.218***	-0.264***	-0.245***	-0.254***	-0.249***	-0.252***	-0.326***	-0.302***	-0.483***
	(0.0521)	(0.0470)	(0.0450)	(0.0506)	(0.0505)	(0.0545)	(0.0451)	(0.0460)	(0.0540)	(0.0599)	(0.0733)
Percent Pop Identified as White	-0.00927	0.0106	0.0356	-0.0254	0.0602	-0.00470	0.0385	0.0695**	0.0426	0.112**	0.224***
	(0.0409)	(0.0352)	(0.0311)	(0.0299)	(0.0313)	(0.0338)	(0.0271)	(0.0266)	(0.0307)	(0.0340)	(0.0366)
Percent Pop Identified as Black	-0.0789	-0.105*	-0.0909*	-0.132***	-0.0994**	-0.164***	-0.108**	-0.0796*	-0.106**	-0.0748	0.119*
	(0.0488)	(0.0436)	(0.0387)	(0.0372)	(0.0368)	(0.0389)	(0.0328)	(0.0340)	(0.0411)	(0.0447)	(0.0569)
Percent Pop Identified as Latino	-0.131***	-0.156***	-0.139***	-0.0986***	-0.160***	-0.163***	-0.156***	-0.151***	-0.187***	-0.246***	-0.180***
	(0.0330)	(0.0319)	(0.0267)	(0.0273)	(0.0368)	(0.0425)	(0.0324)	(0.0317)	(0.0376)	(0.0388)	(0.0393)
Constant	7.952	0.581	-6.443	2.323	11.81	11.96	5.857	-1.240	-4.697	-7.887	-76.02***
	(9.641)	(9.971)	(9.605)	(10.08)	(11.85)	(13.26)	(11.14)	(11.29)	(13.12)	(14.14)	(16.34)
N	578	593	607	604	665	696	688	715	710	725	755
R-sq	0.195152	0.247318	0.266390	0.239602	0.274931	0.238635	0.225021	0.232253	0.259319	0.224987	0.212679

Standard errors in parentheses

* p<0.05, ** p<0.01, *** p<0.001

APPENDIX E: RANDOM EFFECTS AND FIXED EFFECTS MODEL TABLES

Table E1

Random Effects Model Controlled for State

	DeathRate
Levels of Protection	0.738*** (0.0834)
Naloxone Access Laws	3.848*** (0.250)
Gini Index	64.03*** (4.172)
Median Income	0.0000120 (0.0000132)
Percent Pop with High school Dipoma	0.0232 (0.0327)
Percent Pop with Bachelor’s or Higher	-0.287*** (0.0197)
Percent Pop Identified as White	0.0990*** (0.0161)
Percent Pop Identified as Black	-0.00298 (0.0198)
Percent Pop Identified as Latino	-0.149*** (0.0116)
Constant	-13.99*** (3.754)
N	7336
R-sq	

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

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Table E2

Fixed Effects Model Controlled for County

	DeathRate
Levels of Protection	0.419*** (0.0699)
Naloxone Access Laws	2.712*** (0.212)
Gini Index	75.19*** (8.175)
Median Income	0.000175*** (0.0000357)
Percent Pop with High school Dipoma	0.190*** (0.0489)
Percent Pop with Bachelor’s or Higher	0.225*** (0.0451)
Percent Pop Identified as White	-0.200*** (0.0442)
Percent Pop Identified as Black	-0.0162 (0.121)
Percent Pop Identified as Latino	-0.242* (0.0982)
Constant	-31.20*** (6.460)
N	7336
R-sq	0.214322

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

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Table E3

Fixed Effects Model Controlled for County

	LaggedDeathRate
Levels of Protection	0.237*** (0.0624)
Naloxone Access Laws	1.829*** (0.191)
Gini Index	60.88*** (8.765)
Median Income	0.000175*** (0.0000382)
Percent Pop with High school Dipoma	0.203*** (0.0481)
Percent Pop with Bachelor’s or Higher	0.0471 (0.0426)
Percent Pop Identified as White	-0.156*** (0.0448)
Percent Pop Identified as Black	-0.00738 (0.121)
Percent Pop Identified as Latino	-0.147 (0.0979)
Constant	-26.23*** (6.834)
N	6161
R-sq	0.147826

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

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