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The Effect of Naloxone Access Laws on the Type of Referrals and Admin Treatment Settings of Drug Treatment Centers for Opioid Abuse

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Abstract

Opioid overdose is one of the leading health problems in the United States. Since 1999, deaths from drug overdose in the United States have more than doubled. The development of public policies to provide naloxone to the public is crucial in mitigating some of the negative effects of opioid substance abuse. Current economic literature has primarily focused on the relationship between naloxone access laws and opioid overdoses. In this paper, I use a multinomial logit regression to examine the impact of passing a naloxone access law on the type of referrals and admin treatment settings of drug treatment center for opioid abuse. I measure referral source and service setting at admission to publicly funded drug treatment centers using the Treatment Episodes Data Set (TEDS) from 1999 to 2015 and use information on naloxone access laws from the Policy Surveillance Program (PSP). I find that when a naloxone access law is enacted, the probability of a community referral, relative to an individual referral, increases by 37.5% while the probability of a detox setting at admission relative to an ambulatory setting decreases by 49.9%. When a third-party provision is enacted, the probability of a community referral relative to an individual referral increases by 39.4%. If there is a criminal liability provision enacted, the probability of a criminal/court referral, relative to an individual referral, increases by 24.6%. If there is a civil liability provision, the probability of a community referral, relative to an individual referral increases by 28.4% and the probability of a detox setting at admission, relative to an ambulatory setting decreases by 54.5%.

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1. Introduction

Since 1999, drug overdose deaths in the United States have more than doubled (Chen, et al. 2015). Drug overdoses are now the leading cause of injury death in the U.S., surpassing both traffic accidents and gun-related deaths. The opioid epidemic has swept through the U.S. and has been affecting people from all walks of life; ranging from the homeless to the top 2%.

In an effort to deal with the growing opioid epidemic throughout the country, all states, along with the District of Columbia and Puerto Rico[1] have passed variations of the Naloxone Access Law (NAL), allowing laypersons to administer naloxone hydrochloride (naloxone), an opioid receptor, to a person experiencing an overdose. The first state to pass such a law was New Mexico in 2001, with other states quickly following suit. Some states have even issued a standing order allowing pharmacists to dispense naloxone to people without a prescription (Non-Prescription Standing Order).

Naloxone programs have generally been supported by medical professionals and lawmakers from both political parties. However, there are critics (Dolac and Mukherjee 2019) who believe that easy access to naloxone could unintentionally increase opioid abuse by saving the lives of active drug users who will then continue to abuse opioids. The belief is that it will reduce the risk per use and will make opioid use more appealing. In April of 2016, Governor LePage of Maine vetoed a Non-Prescription Standing Order, stating that "naloxone does not truly save lives; it merely extends them until the next overdose" (Newman 2016). His veto was later overturned by the Maine legislature. Researchers have actually found that the adoption of a NAL is associated with a 9 to 11 percent reduction in opioid-related deaths (Rees 2017),

[1] Puerto Rico has been excluded from this study

Naloxone has been inexpensively available since 1985, but over the past few years, the growing demand has led to an increase in price. Currently, the price of naloxone hovers around $20-$40 for the generic option, but prices continue to rise (Newman 2016). This could present a barrier to those seeking the life-saving drug. If the price of naloxone continues to increase, limiting the accessibility to the general public, there is a possibility that it will not be as effective in reducing opioid related deaths and potentially deter treatment admission.

In this paper I estimate the effect of NALs on the type of referrals and treatment setting at admission at a publicly funded treatment center for opioid abuse. The purpose of this study is not to find out if passing a naloxone access law and the provisions increase or decrease admissions to treatment centers, but to see if these laws change the types of referrals and settings for people admitted to treatment centers. I use a maximum likelihood (polytomous) logit regression and data from the Treatment Episode Data Set and the Policy Surveillance Program.

I find that when a state passes a Naloxone Access Law, this increases the probability of a community referral relative to an individual referral by 37.5%. Adding a third-party provision increases the probability of a community referral relative to an individual referral by 39.4%. Adding a civil liability provision, increases the probability of a community referral relative to an individual referral by 28.4%. These increases are likely due to the fact that naloxone is more accessible to organizations or groups that can easily identify people at risk of overdoses (shelters, Narcotics Anonymous, etc.). Now that they are able to get a hold of naloxone and are free from any criminal prosecution for administering naloxone, they can help prevent potential overdose deaths and urge those people to seek treatment.

Enacting a provision for criminal liability increases the probability of a criminal/court referral, relative to an individual referral, by 24.6%. Without fear of legal consequences, lay administrators are more likely to call emergency responders after administering naloxone to a person experiencing an overdose. This gives the victim more chance of getting treatment through referral from a criminal or court system.

When a naloxone access law is put into effect, the probability of a detox setting at admission relative to an ambulatory setting decreases by 49.9%. When there is a civil liability provision, the probability of a detox setting at admission relative to an ambulatory setting decreases by 54.5%. These changes are likely due to the fact that more administrations are happening outside of medical offices are people are not entering treatment centers for detox.

2. Background

Since 2001, a number of cities and states in the United States have initiated other programs and/or policies in combination with NALs to combat the opioid epidemic. Many states have prescription drug monitoring programs (PDMPs) to improve opioid prescribing and protect patients at risk. PDMPs collect information on all filled prescriptions for controlled substances to identify and deter drug abuse and identify persons addicted to prescription drugs. There is strong evidence that PDMPs lead to a reduction in opioid prescribing by physicians (Bao, et al., 2016).

As noted above, all states, the District of Columbia and Puerto Rico have passed some version of a NAL. Naloxone reverses the potentially fatal respiratory depression caused by heroin and other opioids and can be administered via intramuscular, intranasal, intravenous, or subcutaneous routes (Heller, et al., 2007). It has no agonist properties and therefore cannot be abused and has minimal potential for misuse.

Some states have allowed naloxone to be prescribed to third parties – people who might witness an overdose, including friends and family of people who use drugs. Most overdoses are witnessed by others (Tracy, et al., 2005) and more accessibility to naloxone gives witnesses the opportunity to take on the role of a responder. Naloxone can be administered with little to no formal training (Wheeler, et al., 2015), is safe to use, and is a cost-effective method of reducing overdose deaths. The side effects of naloxone are minimal and include headache, nausea, sweating and vomiting, none of which are life threatening (Boyer, 2012). If administered timely, it can reverse the effects of the overdose and gives the administrator and/or victim time to call trained professionals.

2.1. Related Literature

This paper contributes to a growing literature on policies that address the opioid epidemic. Researchers have examined the impact of various policies and programs like prescription drug monitoring programs (Dave, et. al., 2017) and access to opioid antagonists like naloxone on opioid abuse (Rees, et. al., 2017).

The ongoing opioid epidemic can be, in part, explained by an increase in prescription drug misuse. Over 50 million individuals aged 12 and over have misused[2] prescription drugs in their lifetime (Dave, et. al., 2017). A study done by Schnell, et. al. found that within the same specialty and practice location, physicians who completed their initial training at top medical schools were writing significantly fewer opioid prescriptions annually compared to physicians from lower ranked schools. States have tried to put more control on opioid prescribing with PDMPs.

Dave et. al., 2017 estimates the impact of PDMPs on prescription drug abuse, using substance abuse treatment admissions as a measure of abuse. They use the Treatment Episode Data Set from 2003-2014 and find that there was no substantial effect on abuse treatment admissions when there was an operational PDMP in place. However, when there was a

[2] Misuse is defined as use for non-medical purposes

mandatory access provision, requiring providers to query the PDMP prior to prescribing a controlled drug, there was a significant reduction in prescription drug abuse with the main reduction shown in young adults aged 18-24.

Existing economic literature on opioid antagonists has focused primarily on the impact they have on opioid overdoses. Rees, et. al., 2017 was the first study to examine the relationship between naloxone access laws and opioid-related deaths. Using cause-of-death mortality data from the National Vital Statistics System from the years 1999-2014, they found that the adoption of a NAL was associated with a 9 to 11% reduction in opioid-related deaths. After 2 years, the effect grew to an average of a 21% reduction in opioid deaths. This effect was apparent even after controlling for a Prescription Drug Monitoring Program. Their paper also focused on Good Samaritan Laws (GSLs), which prove immunity from prosecution for drug possession to anyone who seeks medical assistance in the event of an overdose. The effect of GSLs on opioid-related deaths was comparable in magnitude to the NALs but was not statistically significant.

I use insight gained from this paper to develop a hypothesis for the relationship between naloxone access laws and the type of referrals and treatment setting at admission at a treatment center for opioid abuse.

3. Data and Methods

This study utilizes individual-level data from the Treatment Episodes Data Set (TEDS)[3] that records the type of referrals and treatment settings of all the people admitted for treatment.

[3] U.S. Department of Health and Human Services, Substance Abuse and Mental Health Services Administration, Center for Behavioral Health Statistics and Quality. (2018). *National Survey on Drug Use and Health 2016* (NSDUH-2016-DS0001). Retrieved from https://datafiles.samhsa.gov/

This data is supplemented with state-level Naloxone Access Laws and related provisions from the Policy Surveillance Program (PSP).[4]Descriptions of each data source are below.

3.1. Treatment Episodes Data Set

I obtained individual-level data on substance abuse treatment from the TEDS. The first naloxone access law passed was in New Mexico in 2001. I concentrated on the period between 1999 and 2015 to include a few years of the pre-adoption period. TEDS is a national data system maintained by the Center for Behavioral Health Statistics and Quality, Substance Abuse and Mental Health Services Administration (SAMSHA) that reports annual admissions to substance abuse treatment centers that receive funding from the state or federal government, are certified by the state to provide specialty substance abuse treatment, or are tracked for some other reason. This means that although TEDS is comprised of a significant portion of all admissions (about 67% of the entire population of treatment admissions to all known providers), it doesn't include all annual admissions nationwide. TEDS also doesn't include data on facilities operated by the federal government (including, the Bureau of Prisons, the Department of Defense, and the Department of Veteran Affairs)

It should also be noted that this feature has an important implication for interpreting my findings as the sample is composed of a disproportionate number of individuals who receive substance abuse treatment in a facility that is publicly funded. This leads to my data having a larger proportion of minority and lower income individuals. People with higher socio-economic status will generally attend more private treatment centers.

[4] Center for Public Health Law Research at the Temple University Beasley School of Law. Prescription Drug Abuse Policy System (PDAPS). (2018). *Policy Surveillance Program.* Retrieved from https://j.mp/2JrbffB

TEDS records admissions of those aged 12 and older and includes admission demographics such as age, sex, race, education, employment, etc. and substance abuse characteristics such as time of first use, substances used, number of prior admissions, etc.

The primary units of observation are referral source and service setting at admission. The dataset includes self-referrals, referrals from the justice system, employers and educational agencies for the former, and includes 24-hour detox (inpatient and outpatient), rehab (short term, long term and hospital) and ambulatory (detoxification, non-intensive and intensive) for the latter. From these variables, I created two multinomial variables: referralsetting and adminsetting2, that range from 1-3. Referral source is broken up into three groups: individual referral, court/criminal justice referral and community referral. Admin setting is broken up into three groups: detox, rehab and ambulatory.

3.2. Policy Surveillance Program

The PSP is dedicated to increasing the use of policy surveillance and scientific legal mapping as tools for improving the nation's health. The program addresses the chronic lack of readily accessible, non-partisan information about status and trends in health legislation and policy.

Using the data from the PSP, I created six binary variables indicating: (1) whether the jurisdiction had a naloxone access law; (2) whether prescriptions of naloxone were authorized to third parties; (3) whether pharmacists allowed to dispense or distribute naloxone without a patient-specific prescription from another medical professional; (4) whether a layperson was immune from criminal liability when administering naloxone; (5) whether a layperson was immune from civil liability when administering naloxone and (6) whether the law removes criminal liability for possession of naloxone without a prescription. I then merged this data with the TEDS variables.

All models include time varying observable characteristics of the respondents such as age, education, and marital status. I included a series of indicator variables for the years 1999 to 2015 to help capture some of the national trends such as the reformulation of OxyContin in 2010.[5] I also included a series of indicator variables for each core-based statistical area (cbsa) to capture geographical trends.[6]

3.3. Empirical Model

I estimate the relationship between naloxone access laws and types of referral and treatment service at admission using a multinomial (polytomous) logistic regression model. This model is employed when dependent variables involve three or more categories. Even though the categories are coded as 1, 2 and 3, there is no order to this (i.e. just because 1 < 2 < 3, it doesn't imply that outcome 1 is less than outcome 2 is less than outcome 3). In a multinomial logit model, the coefficients estimated are $\beta^{(1)}$, $\beta^{(2)}$ and $\beta^{(3)}$. The multinomial logit model is outlined in Equations *(1) – (3)*.

$$(1) \qquad Pr(y=1)=\frac{e^{X\beta(1)}}{e^{X\beta(1)}+e^{X\beta(2)}+e^{X\beta(3)}}$$

$$(2) \qquad Pr(y=2)=\frac{e^{X\beta(2)}}{e^{X\beta(1)}+e^{X\beta(2)}+e^{X\beta(3)}}$$

$$(3) \qquad Pr(y=3)=\frac{e^{X\beta(3)}}{e^{X\beta(1)}+e^{X\beta(2)}+e^{X\beta(3)}}$$

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[5] OxyContin was reformulated in 2010 to make the drug resistant to physical and chemical manipulation for abuse by snorting and injecting. It was approved by the FDA in 2011 but it did not meet the agency's standard to be considered abuse-deterrent.

[6] A cbsa is a geographical area that consists of an urban center of at least 10,000 people plus adjacent counties that are socioeconomically tied to the urban center by commuting.

Since there are more than 2 categories, a baseline category needed to be determined. This is done by arbitrarily setting one of $\beta^{(1)}$, $\beta^{(2)}$ or $\beta^{(3)}$ to 0. See Equations *(4)* and *(5)* and *(6)* for outlined where the baseline is equal to 1 ($\beta^{(1)}$=0).

$$(4) \qquad Pr(y=1)=\frac{1}{1+e^{X\beta(2)}+e^{X\beta(3)}}$$

$$(5) \qquad Pr(y=2)=\frac{e^{X\beta(2)}}{1+e^{X\beta(2)}+e^{X\beta(3)}}$$

$$(6) \qquad Pr(y=3)=\frac{e^{X\beta(3)}}{1+e^{X\beta(2)}+e^{X\beta(3)}}$$

There are two primary variables looked at: referralsource and adminsetting2, which are multinomial variables indicating the source of referral and the type of service and treatment setting in which the client is placed at the time of admission or transfer, respectively. These variables range from one to three. Referralsource is separated by individual, court/criminal justice, and community referrals (labeled 1, 2 and 3, respectively). Adminsetting2 is separated by detox, rehab, and ambulatory treatment settings (labeled 1, 2 and 3, respectively).

Using the data from the PSP, I created 6 binary variables indicating whether there was a naloxone law passed in a given state *s* over year *t* and included five relevant provisions. Appendix Table 1 shows the effective dates of when the NAL and the relevant provisions were passed. I ran six separate regressions, one for the NAL indicator and one for each provision. Tables 3-9 show the results for the multinomial logit regressions.

In all regressions, I control for a series of potentially confounding factors such as age, married, male, non-Hispanic black, Hispanic (white is omitted for multicollinearity) and education.

All specifications include an indicator variable for cbsa, which control for any unmeasured heterogeneity across different geographic areas. Time fixed effects are also included in all regressions, which capture unobserved trends in opioid use and related factors common to the entire population, such as the reformulation of oxycontin in 2010.

4. Results

4.1. Summary Statistics

The data of admissions to treatment centers from 1999-2015 has 22,778,352 observations. After cleaning and merging with the data from the policy surveillance program, there are 15,298,691 observations. I focused on a 20% random sample with a fixed seed so that the sample is replicable. Even with a 20% sample, there are over 4.5 million data entries. Table 2 includes descriptive statistics of the variables of interest in the dataset.

TEDS includes data for persons aged 12 and over. Clients who are 11 or younger, or whose age is unknown, aren't included in the data. Clients under 21 years of age were removed from the dataset. Clients between the ages 21-39 consist of a significant portion of all admissions (almost 63%) and as the age increases, the percentage of admission in the sample for that age group decreases. A significant majority of the admissions are composed of males, about 68%. The education group with the largest amount of admissions is 12 years (i.e. high school completion) consisting of almost 45% of all admissions. A majority of the referrals were self-referrals and criminal/court system referrals (both totaling about 85% of all admissions). About 65% of all admissions were ambulatory, which means that most of the clients were freely coming in and out of centers for treatment (i.e. weekly appointments, drug tests, check-ins).

The results shown in this table are not surprising. As expected, the majority of the dataset consists of non-Hispanic white males. This is consistent with studies that show that the highest at-risk population for heroin addiction is non-Hispanic, white males. (Today's Heroin Epidemic, 2015).

Even though all states have passed some type of naloxone access law by 2017, only 22.96% of the sample lived in states where there was a naloxone access law enacted. Since there has never been an event when one of the provisions was passed but no naloxone law was passed, it makes sense that the percentage of the sample living in states where a provision was passed is lower, for all provisions.

Table 1 presents summary statistics for the variables of interest for the period preceding the naloxone access law and for the years after the law went into effect. Sample means for the demographic variables are similar among the treated and control groups with the exception of the amount of Hispanic people and the amount of married people. In NAL states, there were more Hispanic people admitted to treatment abuse centers and less married people.

4.2.Regression Results

Table 2 presents the estimated effects of NALs on referral source (relative to an individual referral) and on treatment setting at admission (relative to an ambulatory treatment setting). The results show that if there was a NAL enacted, the probability of being referred by a court/criminal justice system is 7.7% higher, relative to an individual referral and isn't statistically significant at conventional levels. The probability of a community referral is 37.5% higher, relative to an individual referral and is statistically significant at the 5% level. If there was a NAL enacted, the probability of a detox setting at admission is 50% lower, relative to an ambulatory setting at admission and the probability of a rehab setting at admission is 14.5% higher, relative to an ambulatory setting. Both results are statistically significant at the 5% level.

Table 3 presents the estimated effects of a third-party provision on referral source (relative to an individual referral) and on treatment setting at admission (relative to an ambulatory treatment setting). If there was a third-party provision enacted, the probability of being referred by a court/criminal justice system is 6.8% higher, relative to an individual referral and is not statistically significant. The probability of a community referral is 39.4% higher, relative to an individual referral and is statistically significant at the 1% level. If there was a third-party provision enacted, the probability of a detox setting at admissions is 38.3% lower, relative to an ambulatory setting at admission and the probability of a rehab setting at admission is 5% higher, relative to an ambulatory setting at admission. Neither of these results are statistically significant.

Table 4 presents the estimated effects of a pharmacist dispensing provision on referral source (relative to an individual referral) and on treatment setting at admission (relative to an ambulatory treatment setting). If there was a pharmacist dispensing provision enacted, the probability of being referred by a court/criminal justice system is 13.7% higher, relative to an individual referral and the probability of a community referral is 13.9% higher, relative to an individual referral. Neither of these results are statistically significant at conventional levels. If there was a pharmacist dispensing provision enacted, the probability of a detox setting at admission is 14.8% lower, relative to an ambulatory setting at admission and is not statistically significant. The probability of a rehab setting at admission is 20.4% higher, relative to an ambulatory setting and is significant at the 5% level.

Table 5 presents the estimated effects of immunity from criminal liability for administration of naloxone provision on referral source (relative to an individual referral) and on treatment setting at admission (relative to an ambulatory treatment setting). If there was a criminal immunity for administration provision, the probability of being referred by a court/criminal justice system is 24.6% higher, relative to an individual referral and is statistically significant at the 5% level. The probability of a community referral is 19.2% higher, relative to an individual referral and is not statistically significant. If there was a criminal immunity for administration provision, the probability of a detox setting at admission is 38% lower, relative to an ambulatory setting at admission and the probability of a rehab setting at admission is 5% higher, relative to an ambulatory setting. Neither of these results are statistically significant.

Table 6 presents the estimated effects of an immunity from civil liability for administration of naloxone provision on referral source (relative to an individual referral) and on treatment setting at admission (relative to an ambulatory treatment setting). If there was a civil immunity for administration provision, the probability of being referred by a court/criminal justice system is 20.1% higher, relative to an individual referral and is not statistically significant. The probability of a community referral is 28.4% higher, relative to an individual referral and this result is statistically significant at the 5% levels. If there was a civil immunity for administration provision, the probability of a detox setting at admission is 54.5% lower, relative to an ambulatory setting at admission and is statistically significant at the 1% level. The probability of a rehab setting at admission is .1% higher, relative to an ambulatory setting and is not statistically significant.

Table 7 presents the estimated effects of an immunity from criminal liability for possession of naloxone provision on referral source (relative to an individual referral) and on treatment setting at admission (relative to an ambulatory treatment setting). If there was a criminal immunity for possession provision, the probability of being referred by a court/criminal justice system is 17.7% higher, relative to an individual referral. The probability of a community referral is 28.4% lower, relative to an individual referral. If there was a criminal immunity for possession provision, the probability of a detox setting at admission is 16.3% higher, relative to an ambulatory setting at admission and the probability of rehab setting at admission is 4.3%

higher, relative to an ambulatory setting at admission. It is not surprising that none of these results are statistically significant at conventional levels as only 2.4% of the sample lived in states where there was a provision for immunity from criminal liability for possession of naloxone without a prescription.

4.3.Regression Analysis

Enacting a naloxone access law and/or a third-party provision significantly increases the probability of a community referral relative to an individual referral. States tend to discourage or even outright prohibit the prescription of drugs to a person who is not the intended recipient. By enacting a third-party provision and allowing people other than the drug user a prescription to naloxone, this significantly increases the probability of a community referral relative to an individual referral. Religious organizations, self-help groups dealing with addictions, and shelters will now be able to carry naloxone. These are the types of groups where people at risk for an opioid overdose tend to come to. These organizations can identify people at risk and if necessary, administer naloxone if someone is having an overdose. They can also urge the individual to get help and get them admitted to a treatment center.

Some states have gone even further and enacted a civil liability provision, which gives immunity from civil prosecution for a layperson who administers naloxone. This leads to an increase in the probability of a community referral relative to an individual referral by 28.4%. By removing the possibility for civil prosecution for administering naloxone, the groups mentioned above have even more incentive to keep naloxone and administer when necessary. This provision also has an effect on the service setting at admission.

Enacting a naloxone access law significantly decreases the probability of a detox setting at admission relative to an ambulatory setting, by 49.9%. Including a civil liability provision also decreases the probability of a detox setting relative to an ambulatory setting decreases by over 50%. This could be because now that naloxone is more accessible to the person who abuses opioids and their family and friends, it is less of a risk to allow the client to come in and out of the treatment center (ambulatory). While detox setting at admission might not decrease in general, it does in relation to ambulatory setting which could have increased with the passage of a NAL.

The decrease could also be attributed to an increase in administrations done by laypersons rather than just trained medical professionals. It is easy to assume that there will be more administrations done by laypersons and not just trained medical professionals. Those who are saved from overdoses on opioids by laypersons are less likely to enter a detox program. More administrations of naloxone will occur at home or in other public settings instead of doctor offices, urgent cares or hospitals where that person would then be pushed to enter a detox program. This is not to say that treatment center admissions will decrease, just the type of setting at admission will be altered.

Enacting a criminal liability provision significantly increases the probability of being referred to a treatment center by a court/criminal justice system, relative to an individual referral. Although naloxone is not a controlled substance, it is a prescription drug. People who are in possession of naloxone can administer it to a person having an overdose, can now summon emergency responders without fear of legal consequences. This provision removes the possibility of negative legal action against lay administration and in turn, leads to more court/criminal referrals to treatment admission centers.

5. Limitations

When using the multinomial logit model, the maximum likelihood estimates of the coefficients may be biased if relevant variables have been left out of the specification. These omitted variables can be measured or unmeasured. Although I have included all variables which I thought relevant and that were provided in the dataset, there is always a possibility that there were variables that have been left out of the specification. Some individual level characteristics are missing from the dataset, such as income, employment and household characteristics (English not spoken at home, parents in the workforce, etc.).

In the 2017 study examining the relationship between naloxone access laws and good Samaritan laws and opioid related deaths, Rees, et. al., include many environmental characteristics such as beer tax, cigarette tax, minimum wage, legalization of marijuana, etc. These could possibly have a significant effect if included in my specification.

6. Conclusion

In order to address the exponentially growing opioid epidemic in the United States, every state, the District of Columbia and even Puerto Rico (excluded from this study) have passed a naloxone law, allowing laypersons to administer naloxone to a person experiencing an overdose. The naloxone counteracts the effects of the overdose and restores breathing. Some states have gone even further and have passed provisions allowing prescriptions to third parties (i.e. friends and family of those at risk of an overdose), allowing pharmacists to distribute naloxone without a patient-specific prescription, giving civil and criminal immunity for administration of naloxone and/or possession of naloxone without a prescription.

This study contributes on the effects of naloxone access laws and these provisions, specifically, on the source of referral (criminal/court and community, both relative to the individual referral) and the type of treatment setting in which the client is placed at the time of admission or transfer (detox and rehab, both relative to an ambulatory setting).

I found that passing a naloxone access law significantly increases the probability of a community referral relative to an individual referral. The law also decreases the probability of a detox setting at admission relative to an ambulatory setting at admission but increases the probability of a rehab setting at admission relative to an ambulatory setting. Including a third-party provision significantly increases the probability of a community referral relative to an individual referral. Including a pharmacist dispensing provision increases the probability of a rehab setting at admission relative to an ambulatory setting. Including a criminal liability provision increases the probability of a criminal/court referral relative to an individual referral and increases the probability of a rehab setting at admission relative to an ambulatory setting at admission. Including a civil liability provision increases the probability of a community referral relative to an individual referral and decreases the probability of a detox setting at admission relative to an ambulatory setting.

Naloxone has been supported by medical professionals and lawmakers alike for its ability to save lives from fatal opioid overdoses without medical consequences to the individual administering the drug. Although it is a prescription drug, there is no chance to develop a dependency on it and the side effects are minimal and not life threatening. The relevant laws passed in recent years have made the drug more accessible to people, both those who are at risk for an opioid overdose and those who are not. Laws have been passed to make sure laypersons who administer naloxone are immune from civil and/or criminal prosecution. As long as the price of naloxone does not continue to increase as it has been for the past few years, it will be a cost effective and accessible way to lower deaths from opioid overdoses.

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8. Tables

Table One: Summary Statistics Pre and Post NAL

	(1) Pre NAL	(2) Post NAL
Age 21-24	0.15	0.14
Age 25-29	0.17	0.18
Age 30-34	0.16	0.16
Age 35-39	0.15	0.12
Age 40-44	0.14	0.12
Age 45-49	0.11	0.12
Age 50-54	0.06	0.09
Age 55 and Over	0.05	0.08
Male	0.68	0.69
Non-Hispanic Black	0.22	0.24
Hispanic	0.09	0.16
Married	0.19	0.15
Less than High School	0.06	0.07
Some High School	0.24	0.23
High School Completed	0.45	0.44
Some College	0.19	0.20
College Completed	0.05	0.06

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

Table Two:
Multinomial Logistic Regressions (Naloxone Access Law Treatment)

	2	3	1	2
NAL Treatment	1.077	1.375***	0.501**	1.145**
	(0.101)	(0.143)	(0.163)	(0.074)
Age 25-29	0.768***	0.964*	1.192***	1.075***
	(0.017)	(0.020)	(0.047)	(0.025)
Age 30-34	0.626***	0.884***	1.399***	1.163***
	(0.017)	(0.027)	(0.081)	(0.032)
Age 35-39	0.555***	0.809***	1.636***	1.229***
	(0.021)	(0.036)	(0.111)	(0.039)
Age 40-44	0.496***	0.728***	1.899***	1.245***
	(0.025)	(0.041)	(0.146)	(0.045)
Age 45-49	0.451***	0.689***	2.076***	1.218***
	(0.028)	(0.049)	(0.184)	(0.047)
Age 50-54	0.413***	0.679***	2.188***	1.152***
	(0.030)	(0.051)	(0.221)	(0.054)
Age 55 and Over	0.416***	0.625***	2.070***	1.037
	(0.046)	(0.056)	(0.252)	(0.070)
Male	1.663***	0.606***	1.312***	0.969
	(0.061)	(0.049)	(0.086)	(0.039)
Non-Hispanic Black	1.193*	1.437***	0.876**	1.070
	(0.114)	(0.160)	(0.054)	(0.071)
Hispanic	1.307***	1.259***	0.943	0.824***
	(0.067)	(0.067)	(0.189)	(0.051)
Married	1.085**	0.967	0.597***	0.703***
	(0.040)	(0.071)	(0.031)	(0.027)
Some High School	1.032	1.021	0.914	1.092***
	(0.055)	(0.055)	(0.073)	(0.032)
High School Completed	0.941	0.789***	1.014	1.005
	(0.054)	(0.039)	(0.068)	(0.038)
Some College	0.811**	0.663***	1.017	1.040
	(0.067)	(0.047)	(0.084)	(0.047)
College Completed	0.758*	0.555***	1.032	1.082
	(0.119)	(0.061)	(0.173)	(0.106)

* p<0.1; ** p<0.05; *** p<0.01

Table Three:
Multinomial Logistic Regressions (Third Party Treatment)

	Criminal Referral	Community Referral	Detox Setting	Rehab Setting
Third Party Treatment	1.068	1.394***	0.617	1.050
	(0.114)	(0.157)	(0.206)	(0.067)
Age 25-29	0.768***	0.964*	1.192***	1.074***
	(0.017)	(0.020)	(0.047)	(0.025)
Age 30-34	0.626***	0.884***	1.401***	1.162***
	(0.017)	(0.027)	(0.081)	(0.032)
Age 35-39	0.555***	0.809***	1.636***	1.229***
	(0.021)	(0.037)	(0.111)	(0.039)
Age 40-44	0.496***	0.729***	1.894***	1.246***
	(0.025)	(0.041)	(0.145)	(0.045)
Age 45-49	0.451***	0.690***	2.069***	1.220***
	(0.028)	(0.049)	(0.183)	(0.047)
Age 50-54	0.413***	0.680***	2.180***	1.153***
	(0.030)	(0.051)	(0.220)	(0.054)
Age 55 and Over	0.416***	0.627***	2.062***	1.038
	(0.046)	(0.056)	(0.251)	(0.070)
Male	1.664***	0.606***	1.309***	0.970
	(0.061)	(0.049)	(0.086)	(0.039)
Non-Hispanic Black	1.193*	1.439***	0.873**	1.071
	(0.114)	(0.161)	(0.055)	(0.072)
Hispanic	1.308***	1.261***	0.938	0.827***
	(0.067)	(0.066)	(0.188)	(0.051)
Married	1.085**	0.966	0.597***	0.703***
	(0.040)	(0.071)	(0.031)	(0.027)
Some High School	1.032	1.023	0.911	1.092***
	(0.056)	(0.056)	(0.072)	(0.033)
High School Completed	0.941	0.790***	1.010	1.005
	(0.054)	(0.039)	(0.067)	(0.038)
Some College	0.812**	0.664***	1.012	1.041
	(0.067)	(0.047)	(0.084)	(0.047)
College Completed	0.759*	0.557***	1.026	1.084
	(0.119)	(0.061)	(0.171)	(0.106)

* p<0.1; ** p<0.05; *** p<0.01

Table Four:
Multinomial Logistic Regressions (Pharmacist Dispensing Treatment)

	Criminal Referral	Community Referral	Detox Setting	Rehab Setting
Pharm Disp. Treatment	1.137	1.139	0.852	1.204**
	(0.151)	(0.172)	(0.266)	(0.090)
Age 25-29	0.768***	0.963*	1.193***	1.074***
	(0.017)	(0.020)	(0.047)	(0.025)
Age 30-34	0.626***	0.883***	1.403***	1.163***
	(0.017)	(0.026)	(0.081)	(0.032)
Age 35-39	0.555***	0.808***	1.638***	1.229***
	(0.021)	(0.036)	(0.111)	(0.039)
Age 40-44	0.496***	0.730***	1.891***	1.247***
	(0.025)	(0.041)	(0.144)	(0.045)
Age 45-49	0.451***	0.691***	2.064***	1.221***
	(0.028)	(0.050)	(0.182)	(0.046)
Age 50-54	0.413***	0.681***	2.175***	1.155***
	(0.030)	(0.052)	(0.219)	(0.054)
Age 55 and Over	0.417***	0.628***	2.057***	1.040
	(0.046)	(0.056)	(0.251)	(0.070)
Male	1.665***	0.608***	1.305***	0.971
	(0.062)	(0.050)	(0.088)	(0.040)
Non-Hispanic Black	1.194*	1.443***	0.871**	1.073
	(0.115)	(0.166)	(0.056)	(0.072)
Hispanic	1.311***	1.274***	0.929	0.829***
	(0.069)	(0.069)	(0.191)	(0.052)
Married	1.085**	0.969	0.596***	0.703***
	(0.040)	(0.071)	(0.030)	(0.027)
Some High School	1.033	1.023	0.915	1.093***
	(0.055)	(0.055)	(0.071)	(0.033)
High School Completed	0.941	0.789***	1.015	1.006
	(0.054)	(0.039)	(0.067)	(0.038)
Some College	0.813**	0.665***	1.014	1.042
	(0.067)	(0.046)	(0.083)	(0.047)
College Completed	0.759*	0.558***	1.028	1.084
	(0.119)	(0.060)	(0.171)	(0.106)

* p<0.1; ** p<0.05; *** p<0.01

Table Five:
Multinomial Logistic Regressions (Civil Liability Treatment)

	Criminal Referral	Community Referral	Detox Setting	Rehab Setting
Crim Liability Treatment	1.246**	1.192	0.620	1.050
	(0.139)	(0.141)	(0.205)	(0.084)
Age 25-29	0.768***	0.963*	1.193***	1.074***
	(0.017)	(0.020)	(0.047)	(0.025)
Age 30-34	0.626***	0.883***	1.402***	1.162***
	(0.017)	(0.026)	(0.081)	(0.032)
Age 35-39	0.555***	0.808***	1.638***	1.229***
	(0.021)	(0.036)	(0.111)	(0.039)
Age 40-44	0.496***	0.730***	1.892***	1.246***
	(0.025)	(0.041)	(0.145)	(0.045)
Age 45-49	0.451***	0.691***	2.066***	1.220***
	(0.028)	(0.050)	(0.183)	(0.046)
Age 50-54	0.413***	0.681***	2.177***	1.154***
	(0.030)	(0.052)	(0.221)	(0.053)
Age 55 and Over	0.416***	0.628***	2.060***	1.039
	(0.046)	(0.056)	(0.253)	(0.070)
Male	1.665***	0.609***	1.305***	0.970
	(0.062)	(0.050)	(0.088)	(0.040)
Non-Hispanic Black	1.194*	1.443***	0.871**	1.072
	(0.115)	(0.166)	(0.055)	(0.072)
Hispanic	1.309***	1.273***	0.930	0.829***
	(0.069)	(0.069)	(0.191)	(0.052)
Married	1.085**	0.969	0.596***	0.703***
	(0.040)	(0.071)	(0.030)	(0.026)
Some High School	1.031	1.022	0.917	1.092***
	(0.055)	(0.055)	(0.071)	(0.033)
High School Completed	0.940	0.789***	1.017	1.005
	(0.054)	(0.039)	(0.067)	(0.038)
Some College	0.812**	0.665***	1.016	1.042
	(0.067)	(0.046)	(0.083)	(0.047)
College Completed	0.758*	0.557***	1.030	1.084
	(0.119)	(0.060)	(0.172)	(0.105)

* *p*<0.1; ** *p*<0.05; *** *p*<0.01

Table Six:
Multinomial Logistic Regressions (Civil Liability Treatment)

	Criminal Referral	Community Referral	Detox Setting	Rehab Setting
Civil Liability Treatment	1.201 (0.168)	1.284** (0.149)	0.455*** (0.139)	0.999 (0.095)
Age 25-29	0.768*** (0.017)	0.963* (0.020)	1.192*** (0.047)	1.074*** (0.025)
Age 30-34	0.626*** (0.017)	0.883*** (0.026)	1.402*** (0.081)	1.162*** (0.032)
Age 35-39	0.555*** (0.021)	0.808*** (0.036)	1.639*** (0.110)	1.229*** (0.039)
Age 40-44	0.496*** (0.024)	0.730*** (0.041)	1.891*** (0.144)	1.246*** (0.045)
Age 45-49	0.451*** (0.028)	0.691*** (0.050)	2.065*** (0.183)	1.220*** (0.046)
Age 50-54	0.413*** (0.030)	0.681*** (0.052)	2.179*** (0.220)	1.154*** (0.054)
Age 55 and Over	0.416*** (0.046)	0.628*** (0.056)	2.062*** (0.254)	1.039 (0.070)
Male	1.665*** (0.062)	0.608*** (0.050)	1.305*** (0.087)	0.971 (0.040)
Non-Hispanic Black	1.193* (0.115)	1.442*** (0.166)	0.873** (0.056)	1.072 (0.072)
Hispanic	1.310*** (0.069)	1.273*** (0.069)	0.930 (0.192)	0.829*** (0.052)
Married	1.085** (0.040)	0.969 (0.071)	0.596*** (0.030)	0.703*** (0.026)
Some High School	1.031 (0.055)	1.022 (0.054)	0.922 (0.069)	1.092*** (0.033)
High School Completed	0.940 (0.053)	0.788*** (0.039)	1.023 (0.066)	1.005 (0.038)
Some College	0.811** (0.067)	0.664*** (0.046)	1.020 (0.081)	1.042 (0.047)
College Completed	0.758* (0.119)	0.557*** (0.059)	1.035 (0.171)	1.084 (0.106)

* p<0.1; ** p<0.05; *** p<0.01

Table Seven:
Multinomial Logistic Regressions (Criminal Possession Treatment)

	Criminal Referral	Community Referral	Detox Setting	Rehab Setting
Crim Possession Treatment	1.177	0.716	1.163	1.043
	(0.235)	(0.165)	(0.280)	(0.142)
Age 25-29	0.768***	0.963*	1.193***	1.074***
	(0.017)	(0.020)	(0.047)	(0.025)
Age 30-34	0.626***	0.883***	1.403***	1.162***
	(0.017)	(0.026)	(0.081)	(0.032)
Age 35-39	0.554***	0.807***	1.639***	1.229***
	(0.021)	(0.036)	(0.111)	(0.039)
Age 40-44	0.496***	0.730***	1.892***	1.246***
	(0.025)	(0.041)	(0.144)	(0.045)
Age 45-49	0.451***	0.691***	2.065***	1.220***
	(0.028)	(0.050)	(0.182)	(0.046)
Age 50-54	0.413***	0.681***	2.177***	1.154***
	(0.030)	(0.052)	(0.219)	(0.054)
Age 55 and Over	0.416***	0.628***	2.060***	1.039
	(0.046)	(0.056)	(0.251)	(0.070)
Male	1.665***	0.608***	1.305***	0.971
	(0.062)	(0.050)	(0.087)	(0.040)
Non-Hispanic Black	1.194*	1.443***	0.872**	1.072
	(0.114)	(0.166)	(0.055)	(0.072)
Hispanic	1.312***	1.273***	0.930	0.828***
	(0.068)	(0.069)	(0.191)	(0.052)
Married	1.085**	0.969	0.596***	0.703***
	(0.040)	(0.071)	(0.030)	(0.026)
Some High School	1.034	1.021	0.919	1.092***
	(0.058)	(0.054)	(0.070)	(0.033)
High School Completed	0.942	0.788***	1.019	1.005
	(0.055)	(0.038)	(0.066)	(0.038)
Some College	0.813**	0.664***	1.017	1.042
	(0.068)	(0.046)	(0.083)	(0.047)
College Completed	0.760*	0.558***	1.030	1.084
	(0.120)	(0.059)	(0.172)	(0.106)

* *p*<0.1; ** *p*<0.05; *** *p*<0.01

9. Appendix

Table One: Effective Dates of NALs and Provisions

State	NAL	ThirdParty	PharmDisp	CrimLiab	CivLiab	CrimPoss
AL	6/10/2015	6/10/2015	6/10/2015	6/10/2015	6/10/2015	-
AK	3/15/2016	3/15/2016	3/15/2016	-	3/15/2016	-
AZ	8/06/2016	8/06/2016	8/06/2016	-	8/06/2016	-
AR	7/15/2015	7/15/2015	7/15/2015	7/15/2015	7/15/2015	-
CA	1/01/2008	1/01/2014	1/01/2014	1/01/2011	1/01/2014	-
CO	5/10/2013	4/03/2015	4/03/2015	5/10/2013	5/10/2013	-
CT	10/01/2003	6/30/2015	6/30/2015	10/012003	10/012003	-
DE	8/04/2014	-	8/04/2014	-	-	-
DC	3/19/2013	2/18/2017	2/18/2017	3/19/2013	3/19/2013	3/19/2013
FL	6/10/2015	6/10/2015	7/01/2016	-	6/10/2015	-
GA	4/24/2014	4/24/2014	4/24/2014	4/24/2014	4/24/2014	-
HI	6/16/2016	6/16/2016	6/16/2016	6/16/2016	6/16/2016	6/16/2016
ID	7/01/2015	7/01/2015	7/01/2015	7/01/2015	7/01/2015	-
IL	1/01/2010	1/01/2010	1/01/2010	1/01/2010	9/09/2015	-
IN	04/17/2015	04/17/2015	04/17/2015	-	04/17/2015	-
IA	5/27/2016	5/27/2016	5/27/2016	-	5/27/2016	5/27/2016
KS	7/01/2017	-	7/01/2017	7/01/2017	7/01/2017	-
KY	6/25/2013	6/25/2013	6/25/2013	6/25/2013	6/25/2013	-
LA	8/15/2015	8/15/2015	8/15/2015	8/15/2015	8/15/2015	6/06/2016
ME	4/29/2014	4/29/2014	10/15/2015	7/29/2016	7/29/2016	-
MD	10/1/2013	10/01/2013	10/01/2015	-	10/01/2015	-
MA	8/02/2012	8/02/2012	7/01/2014	7/01/2014	3/12/2016	8/02/2012
MI	10/14/2014	10/14/2014	3/28/2017	10/14/2014	10/14/2014	10/14/2014
MN	5/10/2014	-	5/10/2014	5/10/2014	5/10/2014	-
MS	7/01/2015	7/01/2015	7/01/2015	7/01/2015	7/01/2015	-
MO	8/28/2016	-	8/28/2016	8/28/2016	8/28/2016	8/28/2016
MT	5/03/2017	5/03/2017	5/03/2017	5/03/2017	5/03/2017	-
NE	5/28/2015	5/28/2015	-	5/28/2015	-	-
NV	10/01/2015	10/01/2015	10/01/2015	10/01/2015	10/01/2015	10/01/2015
NH	6/02/2015	6/02/2015	6/02/2015	6/02/2015	6/02/2015	-
NJ	7/01/2013	7/01/2013	7/01/2013	7/01/2013	7/01/2013	-
NM	4/03/2001	4/03/2001	3/14/2014	9/13/2001	9/13/2001	3/04/2016
NY	4/01/2006	2/01/2007	6/24/2014	6/24/2014	6/24/2014	-
NC	4/09/2013	4/09/2013	4/09/2013	4/09/2013	4/09/2013	-
ND	8/01/2015	8/01/2015	8/01/2015	8/01/2015	8/01/2015	8/01/2015
OH	3/11/2014	3/11/2014	3/11/2014	3/11/2014	-	-
OK	11/01/2013	11/01/2013	11/01/2014	-	-	-
OR	6/06/2013	8/06/2013	6/06/2013	-	6/06/2013	-
PA	12/01/2014	12/01/2014	12/01/2014	12/01/2014	12/01/2014	-
RI	6/18/2012	3/03/2014	3/03/2014	6/18/2012	6/18/2012	3/03/2014

SC	6/03/2015	6/03/2015	6/03/2015	6/03/2015	6/03/2015	-
SD	7/01/2016	7/01/2016	7/01/2016	-	-	-
TN	7/01/2014	7/01/2014	7/01/2014	-	7/01/2014	-
TX	9/01/2015	9/01/2015	9/01/2015	9/01/2015	9/01/2015	9/01/2015
UT	5/13/2014	5/13/2014	5/10/2016	-	5/13/2014	-
VT	7/01/2013	7/01/2013	7/01/2013	7/01/2013	7/01/2013	7/01/2013
VA	7/01/2013	7/01/2013	4/15/2015	-	7/01/2013	-
WA	6/10/2010	6/10/2010	7/24/2015	6/10/2010	7/24/2015	-
WV	5/27/2015	5/27/2015	7/24/2015	6/10/2016	5/27/2015	5/27/2015
WI	4/09/2014	4/09/2014	4/09/2014	4/09/2014	4/09/2014	4/09/2014
WY	7/01/2017	7/01/2017	7/01/2017	7/01/2017	7/01/2017	-