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The Impact of State-Level Naloxone Access Policies on Opioid Related Mortality and Admissions

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ABSTRACT

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Opioids, both prescription painkillers and illegal drugs, were responsible for over 33,000 deaths in the United States during 2015. Naloxone treatment to combat opioid overdoses has been used in hospital settings for decades, and during recent years legislation has expanded training and distribution to first aid responders and high risk groups. Several studies have projected the efficacy of community-based opioid overdose prevention programs (OOPPs) and prescription drug monitoring programs (PDMPs), but few have examined state naloxone access policies. This paper investigates the impact of three state policies – non-patient specific prescriptions, third-party prescriptions, and layperson legal immunity when administering naloxone – on reducing opioid related mortality and treatment admissions. Data is collected from the National Center for Health Statistics, SAMHSA, the National Survey of Substance Abuse Treatment Services (N-SSATS), Legal Science database, and the Behavior Risk Surveillance System. A difference-in-difference method has been adopted. I find that from 1999 until 2017, naloxone access policies, especially non-patient specific prescriptions, have increased opioid mortality and admissions. Issues of moral hazard and policy endogeneity indicate that these results may not be reliable.

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CHAPTER ONE
INTRODUCTION

Drug-related overdose is the leading cause of accidental death in the US and deaths from opioid overdose are significant contributors to these statistics, having quadrupled since 1999 (Public, 2017). According to the Centers for Disease Control and Prevention (CDC), there were 47,055 lethal drug-related overdoses in 2014, the highest rate of deaths from overdose of any year on record. Deaths from opioid overdose accounted for 62% of those fatalities, with 18,893 overdose deaths related to prescription opioids and 10,574 overdose deaths related to heroin (Public, 2017). The US Department of Health and Human Services has recognized opioid related overdose as a major public health concern, resulting in more than 33,000 deaths just in 2015 (Kerensky, Todd, & Walley, 2017). Opioids also cause hundreds of thousands of non-fatal overdoses resulting in exorbitant levels of preventable healthcare expenses each year (Legal, 2017). The economic costs of the heroin and opioid abuse crisis are exorbitantly high, and continue to rise yearly. These drug related costs include increased medical care use, worker absenteeism, lost productivity, and the direct costs of police enforcement and interdiction (Evans, Lieber, & Power, 2018). In addition, there are lost earnings due to mortality.

This paper explores the effect of three state policies designed to decrease opioid fatalities and treatment admissions by promoting greater use and distribution of naloxone medication as opposed to restricting the illicit use of opiates. In this paper, a dynamic difference-in-difference (DD) model is used to evaluate opioid related mortality rate and treatment admission trends over time and between states. I hypothesize that the adoption of naloxone non-patient specific prescription, third-party prescription, and Good Samaritan policies will result in decreasing trends of opioid related mortality and treatment admissions. I also expect a delay or lag in the effects of the increased naloxone access policies. Once a policy has been enacted it will take time

to produce elevated quantities of naloxone, distribute it to newly legalized customers, and train these individuals to properly use the application device. To study this question, I use annual state opioid mortality data from National Center for Health Statistics and opioid treatment admissions data from the National Survey of Substance Abuse Treatment Services (N-SSATS). I find that the adoption of naloxone access policies, have increased average state opioid mortality and admissions, which is opposite to their intended purpose.

This paper seeks to contribute to existing literature by exploring the efficacy of state-level naloxone access policies on opioid mortality and admission outcomes. The content of this paper can potentially help identify the most effective state legislation for preventing opioid overdose and abuse. It will provide vital information to policy makers and government bodies, which will allow them to better allocate funds towards efforts that will be most beneficial to reducing negative opioid outcomes.

The next chapter of this paper provides background information regarding economic factors which affect opioid outcomes and information about the clinical effectiveness of naloxone medication. It also provides an explanation of each of the major policies that will be discussed in this paper. Chapter three reviews literature on community programs and previous legislation designed to limit opioid abuse. A description of the data and empirical methods are presented in chapters four and five respectively. The results are analyzed in section six, with a conclusion presented in chapter seven.

CHAPTER TWO

BACKGROUND

Physical health has declined in recent years coinciding with increases in drug poisoning deaths, often involving opioid analgesics including hydrocodone and oxycodone. Understanding the relationship between local economic conditions and drug-related adverse outcomes is important because the United States is experiencing an epidemic of drug overdose fatalities (Hollingsworth, Ruhm, & Simon, 2017). According to Hollingsworth et al. there is strong evidence that suggests opioid related deaths and emergency department (ED) visits increase during times of economic weakness (2017). Increased availability of prescription opioids and reductions in heroin prices, have created a path of increased drug consumption when economic conditions deteriorate because people attempt to comfort themselves through increased drug abuse. ED visits involving narcotic pain relievers increased 117% between 2005 and 2011, and opioid related ED visits grew by 39.5% from 2006 to 2014. Trends of elevated opioid deaths and ED visits were observed during periods of increased national unemployment rate. These results indicate that a one percentage point increase in the unemployment rate will raise predicted opioid mortality rates by 0.19 per 100,000 people.

Opioid tolerance, dependence, and addiction are all manifestations of brain changes resulting from chronic opioid abuse. The opioid abuser's struggle for recovery is in great part a struggle to overcome the effects of these changes. Brain abnormalities resulting from chronic use of heroin, oxycodone, and other morphine-derived drugs are underlying causes of opioid dependence and addiction (Kosten, Thomas, & George, 2002). Opioids attach to specialized proteins, called mu opioid receptors, on the surfaces of opiate-sensitive neurons. The linkage of

these chemicals with the receptors triggers the same biochemical brain processes that reward people with feelings of pleasure (Kosten, Thomas, & George, 2002).

Repeated exposure to escalating doses of opioids alters the brain so that it functions more or less normally when the drugs are present and abnormally when they are absent. Two clinically important results of this alteration are opioid tolerance (the need to take higher and higher dosages of drugs to achieve the same opioid effect) and drug dependence (susceptibility to withdrawal symptoms) (Kosten, Thomas, & George, 2002). Opioid tolerance occurs because brain cells with opioid receptors gradually become less responsive to opioid stimulation. In the presence of excessive opioids, these cells will reduce the number of mu opioid receptors and require higher doses of the drug to receive the same physiological response (Kosten, Thomas, & George, 2002).

Naloxone's effectiveness as a mu-opioid antagonists and its ability to reverse opioid overdoses is well established in clinical research. Ling, Amass, Shoptaw, Annon, Hillhouse, Babcock, & Brigham (2005) conducted a multicenter randomized trial to investigate and compare the clinical effectiveness of buprenorphine–naloxone (bup-nx) to alternative clonidine treatments for opioid detoxification in inpatient and outpatient community treatment programs. A total of 59 of the 77 (77%) inpatients assigned to the bup-nx condition achieved treatment success criterion compared to eight of the 36 (22%) assigned to clonidine (Ling et al, 2005). Additionally, 46 of the 157 (29%) out-patients assigned to the bup-nx condition achieved treatment success criterion, compared to four of the 74 (5%) assigned to clonidine (Ling et al, 2005). This research provides evidence in support of naloxone use for opioid detoxification.

Although several states still consider naloxone to be a prescription drug, it is not a controlled substance and does not have abuse potential. It is regularly utilized by medical first

responders and can be administered by ordinary citizens with little or no formal training (Legal, 2017). Despite the overwhelming benefits to its use, naloxone is often not available when and where it is needed. Opioid overdoses most often occur when the victim is with friends or family members, but in many cases neither the victim nor his or her companions have the medication on hand. Legal restrictions are at least partially responsible for this lack of access. Several state practice laws prohibit the prescription of naloxone to a person other than the one to whom treatment will be administered. Many states also prevent pharmacies and physicians from distributing naloxone to any individuals with whom the prescriber does not have a prescriber-patient relationship (Legal, 2017). Many medical professionals are wary of dispensing naloxone because of fears of misuse and liability consequences. Compounding this issue, people who witness an overdose may be afraid to call for help due to concerns of being prosecuted for possession of illegal drugs, drug paraphernalia, or other crimes (Legal, 2017).

Naloxone will be most effective when placed in the hands of those individuals most likely to respond to an overdose. New naloxone access laws have simplified the process for obtaining naloxone. These updated laws have expanded naloxone availability and decreased restrictions on those who can purchase, distribute, and administer the drug (Public, 2017). An increasing number of states have allowed third-party prescriptions – permitting naloxone to be issued to third parties, who are not at risk of overdose, for use on someone else. These include close friends of at risk individuals, family members, and professionals working with at risk populations (Naloxone Access, 2018). Nearly all states have also established legal protections for those who distribute, carry, or administer naloxone as permitted by law. These Good Samaritan laws provide laypersons immunity from civil and criminal liability when administering naloxone (Naloxone Access, 2018). Many states have authorized non-patient specific prescriptions

allowing individuals and organizations that meet specific criteria to purchase naloxone without needing to interact with a prescriber beforehand (Naloxone Access, 2018). A variety of models have emerged for non-patient specific prescriptions, but from the viewpoint of the patient these different types of programs are largely non-distinguishable.

As of 2016, fourteen states have made naloxone available over the counter at pharmacies for individuals vulnerable to opioid overdose or members of their families, significant others, or companions. By July 15, 2017, all fifty states and the District of Columbia had passed legislation designed to improve layperson naloxone access. Forty states and the District of Columbia have also passed Good Samaritan laws that provide some protection from arrest or prosecution for individuals who treat or report an overdose (Legal, 2017). In most cases, considerable educational material and training have been developed for each respective program to ensure that those who administer naloxone in response to an overdose are adequately prepared for safe and effective administration. In 2014, it was reported that more than 150,000 laypersons had received naloxone training and rescue kits resulting in more than 26,000 reported overdose reversals (Public, 2017). Studies have found that increasing access to naloxone among people who use drugs is associated with decreases in overdose deaths and that there is no associated increase in the use of opioids or other addictive substances (Public, 2017).

CHAPTER THREE

LITERATURE REVIEW

There has been an ample amount of research regarding the effectiveness of local community programs that deal with overdose prevention and naloxone utilization. These facilities train individuals to perform proper overdose treatment protocols and help increase the distribution of naloxone within high risk communities. These community programs have been extremely successful, but many struggle to promote contact of emergency medical services (EMS) in the event of an opioid overdose. The fear of legal ramifications has been cited as the primary reason for not calling EMS. Researchers have also examined the impact of state and federal policies which have altered access to opioid prescriptions. Prescription drug monitoring programs and doctor shopping laws have been shown to greatly reduce opioid related mortality rates, but other policies such as Medicare part D have had unintentional effects resulting in greater opioid abuse. Despite its ability to reverse opioid overdoses in both inpatient and non-clinical settings, little research has been completed to investigate the potential benefits of state policies designed to increase access to naloxone. Initial evidence suggests that state naloxone access policies may be able to reduce opioid related mortality by as much as 11%, but additional research is required to confirm these findings.

A: Overdose Prevention and Naloxone Distribution Community Programs

Although naloxone is a highly effective drug, to achieve the best outcomes, it must be used appropriately in combination with other life saving interventions. Various community programs have been designed to educate people about proper naloxone use and overdose treatment protocols. Despite these efforts to educate people, there have been many cases in which bystanders did not administer naloxone or call EMS after witnessing an opioid overdose

because they feared legal repercussions. Clark, Wilder, and Winstanely (2014) conducted a systematic review of nineteen community opioid overdose prevention and naloxone distribution programs (OOPPs). The researchers' analysis of existing nonrandomized studies suggests that bystanders, especially opioid users, will use naloxone to reverse opioid overdoses when properly trained, and OOPP is effective in addressing opioid abuse. It has been recognized that most OOPP participants do not call EMS when they witness an overdose. Additional research has been suggested to investigate whether laws that provide civil and criminal protection for bystanders would result in increased notification of EMS during an overdose occurrence.

To evaluate the effectiveness of these community education programs Strang, Manning, & Mayet (2008) examined the impact of OOPP training on the knowledge and confidence of opiate users in managing overdoses. The researchers noted statistically significant improvements in knowledge of risk factors for overdose, overdose signs, appropriate responses to overdose, and use of naloxone immediately after OOPP training. Three months after the initial training, 78% of participants demonstrated retention of overdose management knowledge. These overdose management programs can train opiate users to execute appropriate actions to assist the successful reversal of a potentially fatal overdose. The researchers suggest future studies that examine whether public policy of wider overdose management training and naloxone provision could reduce the extent of opiate overdose fatalities, particularly at times of recognized increased risk.

B: Opioid Prescription Policies

Federal, state, and local governments have enacted a range of policies designed to combat nonmedical use of prescription opioids. The most common and well-studied policy is the mandatory use of prescription drug monitoring programs (PDMPs). Such programs require retail

pharmacists to enter information about controlled substance prescriptions and recipients into an electronic database within a specific period of time, typically 7 to 14 days (Popovici, Maclean, Hijazi, & Radakrishnan, 2018). Healthcare providers can access this database to determine if a patient is engaging in doctor shopping behavior – visiting several physicians to obtain multiple prescriptions for otherwise illegal drugs. Numerous studies suggest that PDMPs have been the best deterrent in the attempt to reduce prescription opioid abuse. Evidence on the effectiveness of other laws designed to address nonmedical use of prescription opioids is limited (Popovici et al., 2018).

Healthcare providers who regularly conspire in the dispensing of prescription opioids outside the scope of prevailing medical standards or in violation of state laws are viewed by policymakers as a key contributing factor to the prescription opioid epidemic (Popovici et al., 2018). Nine states have enacted pain management clinic laws with the objective of reducing providers' ability to prescribe opioids for use beyond acceptable medical standards. Popovici et al. (2018) used a difference-in-difference (DD) regression model to study the effect of pain management clinic and doctor shopping laws on state opioid outcomes. On average, pain management clinic laws reduced prescription opioid overdose deaths by 9.6%, doctor shopping law reduced prescription opioid overdose deaths by 8.5%, and the implementation of a PDMP programs reduced prescription opioid overdose deaths by 4.8%.

Opioids have legitimate medical functions, but improving access to these potentially deadly drugs may increase abuse rates. Powell, Pacula, and Taylor (2015) used the Treatment Episode Data Set (TEDS) to study annual opioid abuse treatment admissions by state following the implementation of Medicare Part D. The researchers’ estimates imply that a 10% increase in medical opioid distribution through Medicare Part D lead to a 7.4% increase in opioid related

deaths and a 14.1% increase in treatment admission rates for the Medicare-ineligible populations (Powell et al., 2015). Medicare Part D increased opioid utilization for the 65+ population. This increase in utilization led to significant growth in the overall supply of opioids in high elderly share states relative to low elderly share states, but the expansion in opioid supply through Medicare Part D also resulted in an escalation in opioid related treatment admissions and opioid related mortality among the Medicare-ineligible population. This implies that increases in opioid distribution through Medicare Part D may be causing a spillover of these drugs into populations that are not Medicare beneficiaries and an increased diversion of prescription opioids for nonmedical purposes.

C: Impact of OxyContin Reformulation

Evans, Lieber, & Power (2018) examined how changes to the reformulation of OxyContin impacted the subsequent rise in heroine abuse and mortality rates. The paper shows that between 1999 and 2009, opioid death rates were rising rapidly but heroin death rates were much lower and increasing slowly. Between 2010 and 2014, heroin death rates increased by a factor of four while opioid death rates remained fairly flat. The researchers attributed this rapid rise in the heroin mortality rates to the 2010 reformulation of OxyContin. The makers of OxyContin, Purdue Pharmaceutical, removed the existing drug from the market and replaced it with an abuse-deterrent formulation (ADF) that made it more difficult for the drug to be abused. This made the drug far less appealing to opioid addicts and led many to shift to heroin as a potent substitute that was readily available and cheaper in cost. Heroin deaths began rising during the month following the distribution of the reformulated drug. The reformulation did not generate a reduction in combined heroin and opioid mortality because each prevented prescription opioid death was replaced with a heroin casualty. Efforts to restrict opioid prescriptions may not

decrease opiate overdose and mortality because abusers will turn to heroine as an affordable alternative. Legislators should focus on improving opioid treatment, prevention, and access to naloxone as these are likely the best means to counteract overdoses.

D: Naloxone Access Policies

In an effort to address the opioid epidemic, the majority of states have recently passed some version of a naloxone access law (NAL) or a Good Samaritan law (GSL). The study conducted by Rees, Sabia, Latshaw, & Dave (2017) is the first to examine the effect of these NALs and GSLs on opioid related casualties. The researchers utilized a difference-in-difference model to examine temporal and geographic variation in the passage of NALs and GSLs to gain a better understanding of their effects. Using data from the National Vital Statistics System multiple cause-of-death mortality files for the period 1999-2014, the researchers have found that the adoption of a NAL is associated with a 9 to 11 percent reduction in opioid related fatalities. The estimated effect of GSL on opioid related deaths is of comparable magnitude, but not statistically significant at conventional levels (Rees et al., 2017). The relationship between NALs and opioid related deaths that do not involve heroin appears to be stronger than the relationship between NALs and heroin related deaths. This indicates that NALs are more effective at preventing overdoses from prescription opioid painkillers than illicit drugs. Critics and supporters of the laws debate whether NALs and GSLs benefit drug users and reduce mortality rates. Many believe they will promote greater drug use, but the researchers have discovered little evidence to suggest that these laws increase the recreational use of prescription painkillers (Rees et al., 2017).

CHAPTER FOUR

DATA

A: Outcome Measurements

In order to assess the issue of opioid abuse and misuse, I focus on two broad measures of opioid related outcomes: treatment admissions (2002–2017) and state-level overdose mortality from opioid medications (1999–2017). Due to the recent rise in heroin use, particularly in response to a 2010 reformulation of OxyContin, I am considering treatment admissions and overdose mortality for a combined category of heroin and prescription opioids, which together will be referred to as opiates. All data variables are measured by state and year. Washington D.C. has also been included in the analysis of each state.

Opioid related mortality is measured as the number of annual deaths from prescription opioids and heroine per 100,000 populations. The second dependent variable is the number of opioid related treatment admissions by state and year per 100,000 populations. Opioid related mortality from 1999 to 2017 is obtained from the National Center for Health Statistics. My focus is on estimating the impact of NALs and GSLs on drug overdose deaths involving opioids identified and defined by the *International Classification of Diseases, Tenth Revision* multiple-cause-of-death codes: T40.0 (opium), T40.1 (heroin), T40.2 (other opioids), T40.3 (methadone), T40.4 (other synthetic narcotics), and T40.6 (other unspecified narcotics). This is useful for creating operational definitions for measurements of opioid related mortality rates. It should be noted that the ICD-10 defines the term “narcotic” to include both cocaine derivatives and opioids, so that some portion of the deaths identified by the multiple cause-of-death code T40.6 could have been caused by cocaine. Deaths from cocaine use represent only a small fraction of total opioid related fatalities. A total of 29,650 opioid related deaths occurred in the United

States in 2014, but only 1,635 (5.5 percent) involved unspecified narcotics and no other type of opioid (National, 2017).

Mortality rates due to drug overdoses are reported per 100,000 population and are based on April 1st bridged-race census counts for 2000 and 2010, on July 1st bridged-race estimates for 1999 and 2001–2009, and on vintage 2015 post census estimates for 2011–2017. From 1999 to 2017, almost 218,000 people died in the United States from overdoses related to prescription opioids. Overdose deaths involving prescription opioids were five times higher in 2017 than in 1999 (Wide-ranging, 2016). Mortality rates from prescription opioids were highest in the states of West Virginia, Maryland, Kentucky, and Utah (Scholl et al., 2018).

Opioid related treatment admissions data from 2002 to 2017 was obtained from the National Survey of Substance Abuse Treatment Services (N-SSATS), which is an annual survey of facilities providing substance abuse treatment conducted by the Substance Abuse and Mental Health Services Administration (SAMHSA). The N-SSATS collects data on the location, characteristics, services offered, and number of clients in treatment at alcohol and drug abuse treatment facilities. My interests are in estimating the effects of non-patient prescription, third-party prescription, and Good Samaritan laws on opioid related treatment admissions throughout the 50 states and the District of Columbia.

B: Data Summary

From 1999 to 2017 an average of 7.925 ± 5.484 per 100,000 people living in the US died from opioid overdose or other opioid related complications. In 2017, West Virginia had the highest recorded state opioid related mortality rate at 45.873 deaths per 100,000 people living in the state. Conversely, 1999 Iowa had the lowest recorded state opioid related mortality rate at 0.514 deaths per 100,000 people.

Annual admissions rates to opioid treatment programs also tend to vary greatly from state to state as well as year to year. During the period from 2002 to 2017 – excluding 2014 – the national average for opioid related admission was 115.224 ± 103.609 patient admissions per 100,000 people. State treatment admission rates were highest in 2015 Rhode Island. 715.208 people per 100,000 population in Rhode Island were admitted for opioid overdose or related complications. In 2013, South Dakota had the lowest admission rates of 0.119 people per 100,000 population.

Between 1999 and 2017, several states enacted legislation with the intent to reduce opioid related admissions and mortality. Previous studies have examined the effects of prescription drug monitoring programs (PDMP) and pain management clinic laws (PMCL) on opioid abuse outcomes. Implementation of these laws has resulted in a significant reduction in opioid related admission and mortality rates for many states. Between 1999 and 2017 an average of 68.717% and 7.904% of states had passed PDMP and PMCL legislation respectively. By 2014, every state with the exception of Missouri required physicians and pharmacies to participate in prescription drug monitoring programs. It is important to note that there have been rumors that Missouri's state legislators will propose a plan to implement its own statewide drug monitoring program by the end of 2019 (Hauswirth, 2018).

Little is currently known about the effects of legislation designed to promote naloxone use and accessibility. Non-patient specific prescription laws (NPL), third-party prescription laws (TPL), and Good Samaritan laws (GSL) are meant to increase naloxone availability with the hope that this will reduce the number of preventable admissions and deaths due to opioid overdose. On average, between 1999 and 2017, 18% of states had implemented NPLs, 22.401% of states had implemented TPLs, and 19.365% of states had implemented GSLs. Illinois was the

earliest adopter of NPLs, and the second adopter of TPLs as well as GSLs in 2010. New Mexico was the earliest adopter of TPLs and GSLs in 2001.

All state-year-level demographic controls were obtained from the CDC's BRFSS database including statistics for age, gender, race, education level, employment, income level, marital status, smoking status, and binge drinking. This evaluation was conducted with a test group between the ages of 18 and 65. All individuals below the age of 18 or above the age of 65 have been excluded. Between 1999 and 2017, approximately 6.435% of the US population was between the ages of 18 and 24, 17.460% of the population was between the ages of 25 and 34, 22.709% of the population was between the ages of 35 and 44, 27.108% of the population was between the ages of 45 and 54, and 26.288% of the population was between the ages of 55 and 64. On average, 47.061% of the US population was male and 81.869% was white. On average, 44.588% of people had a bachelor's or advanced degree in higher education, 28.025% of people had some college education, 23.156% had a high school education, and 11.625% did not complete high school. The average unemployment rate between 1999 and 2017 was 5.044%. On average, 77.861% of the population was employed and the remaining 17.095% was not considered part of the labor force. On average, only 38.859% of households earned more than $75,000 each year while more than 17% of households had an annual income less than $25,000. Approximately 17% of US households would be in poverty based on the 2019 poverty line, which sets the poverty level at $25,750 annual income for a four person household (2019 Poverty, 2019). 59.314% of people were married and 19.174% were divorced. On average, 21.617% of the US population smoked and 10.928% binge drank within the last 30 days.

CHAPTER FIVE

EMPIRICAL MODEL

Independent variables are broken down into three categories: naloxone policies of interest, other policy controls, and demographic characteristics. The Legal Science dataset provides details on state policies regarding naloxone administration and overdose prevention. For the purpose of this paper, I am interested in evaluating the effects of three specific policies on opioid related mortality and treatment admission outcomes. I use a series of dummy variables to indicate whether a state allows prescriptions of naloxone to third-parties, whether pharmacists are allowed to dispense or distribute naloxone without a patient-specific prescription from another medical professional, and whether a layperson is immune from criminal liability when administering naloxone. If a state has a law allowing one of these policies in year "t" then the respective dummy variable will receive a value of one. If a law allowing a policy has not been enacted in year "t" then the dummy variable for state "s" in year "t" will receive a value of zero.

Other control policies include PDMP must access laws and pain management clinic laws (PMCL). If physicians are required to access PDMP records before writing a prescription for an opioid in state s and year t then the *PDMP* dummy variable will be one. Otherwise the variable will be zero. Similarly states with PMCL policies in year t will have a dummy variable of one while states without PMCL policies will have a dummy variable of zero.

In this paper, a dynamic difference-in-difference (DD) model is used to evaluate temporal and geographic variation in the passage of NALs and GSLs to gain a better understanding of their effects on opioid related mortality rate and treatment admission. Specifically, we estimate the following baseline Poisson regression:

(1) $$Y_{st} = \beta_0+\beta_1*NPL_{st}+\beta_2*TPL_{st}+\beta_3*GSL_{st}+\beta*X_{st}+\theta_s+\tau_t+\Omega_{st}+\epsilon_{st}$$

where Y_{st} represents an opioid outcome – either the expected number of opioid related deaths or the expected number of opioid related treatment admissions in state s and year t. The independent variables of interest are NPL_{st}, TPL_{st}, and GSL_{st} where NPL_{st} is a dummy variable equal to one if a non-patient specific prescription law was in effect in state s and year t and equal to zero otherwise. The indicators TPL_{st} and GSL_{st} are defined analogously for third-party prescription and Good Samaritan laws respectively. The inclusion of state fixed effects, represented by the term θ_s, ensures that the estimates of β_1, β_2, and β_3 are identified using within-state variation. The year fixed effects, represented by τ_t, account for common shocks to the opioid related deaths caused by such factors as the reformulation of OxyContin in 2010 or changes in drug enforcement priorities at the federal level. State-specific linear time trends (Ω_{st}) are also used to control for time-varying, unobservable state characteristics. I interact state fixed effect with a linear time trend that takes on a value of one for 2002, two for 2003, and so forth. ε_{st} is the error term.

In subsequent regressions, policy and demographic indicators are added to the vector of state characteristics, X_{st}. Policy indicators such as *PDMP* and *PMCL* are equal to one if there is a relevant law operating in state s and year t. There is reasonably strong evidence that the implementation of a PDMP and PMCL reduces opioid prescriptions and drug treatment admissions (Haegerich et al. 2014; Bao et al. 2016). Although, the evidence with regard to PDMPs and opioid related deaths is decidedly mixed (Johnson et al. 2011; Reifler et al. 2012). X_{st} also includes demographic controls including age, sex, race, education, and marital status taken from the Behavioral Risk Factor Surveillance System (BRFSS).

CHAPTER SIX

RESULTS

A: Sample Analysis – Opioid Overdose Mortality

The beta-coefficients for the NPL_{st}, TPL_{st}, and GSL_{st} dummy variables indicate the average change in opioid related mortality per 100,000 people in state s at year t when the law has been enacted within the state. It was expected that states with non-patient prescription (NPL), third-party prescription (TPL), and Good Samaritan laws (GSL) would experience lower average opioid mortality rates. Table 2 presents the results on opioid related mortality using the full sample. As shown in Column 1, none of these policies have any effect on opioid mortality. In Column 2, I exclude the control for smoking and binge drinking because they might be one of the mechanisms in which these policies affect opioid mortality. I find that the results are similar to Column1 – none of the policies have any effect on opioid related mortality.

States that passed an NPL were also very likely to have passed TPL and GSL legislation. Columns 3, 4, and 5 examined the impacts of each policy variable separately due to concerns of high levels of multicollinearity (Table 2). Columns 3 and 4 indicate non-patient specific prescription and third-party prescription policies increased mortality, but Column 5 indicates that Good Samaritan policies did not significantly impact opioid mortality rates. On average, NPLs increased a state's opioid related mortality rate by 1.869 ± 0.884 people per 100,000 population (p-value < 0.05). On average, TPLs increased a state's opioid related mortality rate by 1.321 ± 0.660 people per 100,000 population (p-value < 0.1).

B: Sample Analysis – Opioid Related Treatment Admissions

Table 3, Columns 1 to 6 contain beta-coefficients for the NPL_{st}, TPL_{st}, and GSL_{st} dummy variables, which indicate the average change in opioid related treatment admissions per 100,000

people in state s at year t when the law has been enacted within the state. It was expected that states with non-patient prescription (NPL), third-party prescription (TPL), and Good Samaritan laws (GSL) would experience lower average opioid admission rates. According to the Column 1 results, states which enacted the NPLs experienced a significant increase in opioid admission rates. On average non-patient specific prescription laws increased a state's opioid related treatment admissions by 33.137 ± 14.682 admissions per 100,000 people (p-value < 0.05). Changes due to TPL and GSL legislation were not statistically significant (Table 3, Column 1).

Column 2 examines the impact of smoking and binge drinking on opioid admission rates. As with mortality, removal of the *smoker* and *binge_drink* variables did not significantly alter the beta-coefficients or the standard error for any of the policy variables of interest. Multicollinearity between NPL_{st}, TPL_{st}, and GSL_{st} is an issue for predicting admission as well as mortality outcomes. Columns 3, 4, and 5 contain results for regressions when NPL_{st}, TPL_{st}, and GSL_{st} are separated (Table 3). In Column 3, non-patient specific prescription laws increased a state's opioid related treatment admissions by an average of 29.246 ± 15.096 admissions per 100,000 people (p-value < 0.1). Separating the three policies lowered the NPL_{st} beta-coefficient and its significance level (Table 3, Column 3). Changes due to TPL and GSL legislation were still statistically insignificant (Table 3, Columns 4 and 5).

C: Subsample Analysis – Opioid Overdose Mortality and Treatment Admissions

While the initial results may not have been very substantial or significant for the sample population, it is possible that NPL, TPL, and GSL could have a greater impact on specific groups within the sample. Age, income, and education status are all potential factors which may influence the effectiveness of naloxone access policies. The rates of drug overdose deaths have increased from 1999 to 2017 for all age groups studied, but adults age 35-44 and 45-54

demonstrated significantly higher rates of drug overdose fatalities than any other age group (Figure 1). Individuals age 35-54 are more likely to die from an opioid overdose than any other age group. These individuals are also most likely to receive the maximum benefit from increased naloxone access. Analyzing and comparing the results presented in Table 4, Columns 1 to 6 indicate that the effects of NPL, TPL, and GSL on opioid related mortality are very similar to those presented in Table2, Columns 3 to 5. Changes in opioid mortality rates in response to naloxone access policies do not significantly vary between the various age groups.

There is strong evidence that suggests opioid related deaths and ED visits increase during times of economic weakness (Hollingsworth et al., 2017). While research has mainly focused on the relationship between opioid overdose and unemployment rate trends, it is possible that low income groups may also be highly susceptible to opioid overdose as well as benefit more from naloxone access policies. Table 5, Columns 1 to 3, examines the impact of NPLs, TPLs, and GSLs for a subsample of households with an annual income less than $25,000. The results for low income households do not meet expectations as they are very similar to those for the whole sample population. Table 5 results suggest that income level will not impact changes in opioid mortality rates in response to naloxone access policies.

Studies focusing on trends in the 1990s and 2000s highlight stagnating life expectancy gains among less educated subgroups, particularly for non-Hispanic white women, and continued improvements among more educated subgroups (Ho, 2017). Increasing disparities in life expectancy gains among the less educated coincided with the rise of opioid overdose mortality that initiated in the late 1990's, following FDA approval of the opioid pain reliever OxyContin. Among college graduates, drug overdose death rates have increased over time, but in the most recent period they are still lower than rates observed in the first recorded period for the least

educated (Ho, 2017). Education level may play a role in estimating potential risk to opioid overdose. Lower education groups may be more likely to overdose, but these subgroups may also receive greater benefit from NPL, TPL, and GSL policies. Table 5, Columns 4 to 6, examine the impact of NPL, TPL, and GSL for a subsample of individuals with less than a bachelor's level of education. The results are very similar to those for the whole sample population. These results suggest that education level likely does not impact the effect of naloxone access policies on opioid mortality rates.

A complete subsample analysis was conducted for opioid mortality outcomes to access whether specific subgroups within the sample population would respond differently to NPL, TPL, and GSL policies resulting in improved mortality outcomes. A similar analysis was completed for opioid related treatment admissions, but no significant changes in the impacts of naloxone access policies were observed. To see the results of this analysis please refer to Tables 6 and 7, Columns 1 to 6.

CHAPTER SEVEN

DISCUSSION

A: Multicollinearity

A key goal of regression analysis is to isolate the relationship between each independent variable and the dependent variable. The interpretation of a regression coefficient is that it represents the mean change in the dependent variable for each one unit change in an independent variable when all of the other factors are held constant**.** The idea is to be able to change the value of one independent variable and not the others to observe direct effects of each independent variable on the one that is dependant. However, when independent variables are correlated, it indicates that changes in one are associated with shifts in another**.** This is known as multicollinearity. The stronger the correlation, the more difficult it is to change one variable without changing another. Multicollinearity makes it difficult for a model to estimate the relationship between each independent variable and the dependent variable separately because the independent variables tend to change in unison.

Multicollinearity causes coefficient estimates to change drastically based on which independent variables are included in the model, and the coefficients become very sensitive to small changes. Multicollinearity also reduces the precision of the estimate coefficients, which weakens the statistical power of the regression model. Due to the multicollinearity which exists between NPL_{st}, TPL_{st}, and GSL_{st} policy variables, it is difficult to trust p-values to identify results that are statistically significant. States that have adopted one of the naloxone access policies are very likely to adopt the other policies. This makes it extremely difficult to determine whether the observed coefficients for NPL_{st}, TPL_{st}, and GSL_{st} are the result of adopting each specific policy or the combined effect of multiple policies.

B: Moral Hazard and Endogeneity

States that have adopted any combination of the non-patient specific prescription, third-party prescription, or Good Samaritan laws for naloxone were expected to experience reduced opioid overdose mortality rates and encounter fewer opioid related treatment admissions. While these laws have reportedly increased naloxone availability, my results indicate that NPL and TPL laws have also increased the average number of opioid related mortalities (Table 2). States which have adopted NPLs have also experienced increases in opioid treatment admissions (Table 5). It is strange that these laws designed to improve opioid outcomes would have such negative effects on the substance abuser population.

Two possibilities exist which could explain these unexpected results. First, increased access to naloxone due to adoption of these policies could have encouraged greater opioid abuse, resulting in additional opioid related admissions and fatalities. As naloxone became more widely available in each state, the immediate risk associated with opioid abuse would be lowered causing greater recreational use of prescription medications and illicit drugs. Increased access to naloxone may have created a moral hazard situation, in which the extra level of safety provided by naloxone promoted increased risky behavior with opioid drugs. This scenario is not very likely because if a naloxone moral hazard existed significant increases in mortality and admissions would be associated with all three policy variables – not only NPL.

There is also a possibility that states with high levels of opioid fatalities and admissions are much more likely to adopt naloxone access policies than states with lower previous mortality and admission rates. This would create an endogeneity issue in which a state's opioid related mortality or admissions for the previous year are highly correlated with the independent policy variable for the current year. In this way, states that have a history of high mortality or

admissions will be more likely to adopt NPL, TPL, or GSL policies. This will affect future mortality and admission rates, which will ultimately affect the continued use or adoption of future policies. In order to evaluate potential issues of endogeneity, I estimate the following equation: $NPL_{st} = \beta_0 + \beta_1 * Y\_lag_{st} + \epsilon_{st}$, where NPL_{st} is a measure of the probability that state s will adopt a non-patient specific prescription law in the year t. Y_lag_{st} represents an opioid outcome – either mortality or treatment admissions – in state s and the year t-1. I find that the previous year's opioid overdose mortality and treatment admissions are significantly correlated with the current year's NPL_{st}, which indicates that the adoption of non-patient specific prescription policies is non-random.

CHAPTER EIGHT

CONCLUSION

Significant research has determined that the adoption of NPLs and TPLs is associated with a 9 to 11 percent reduction in opioid overdose mortality. The estimated effect of GSL on opioid related deaths is of comparable magnitude, but not statistically significant at conventional levels (Rees et al., 2017). The relationship between naloxone access policies (NALs) and opioid related deaths that do not involve heroin appears to be stronger than the relationship between NALs and heroin-related deaths. This indicates that NALs may be more effective at preventing overdoses from prescription opioid painkillers than illicit drugs. Critics and supporters of the laws debate whether NALs benefit drug users or reduce mortality rates. Many believe increased accessibility to naloxone will promote greater recreational opiate use, but these concerns pale in comparison to the potential benefit of increased naloxone access (Rees et al., 2017). NAL policies are expected to greatly reduce the number of opioid related deaths, and prevent avoidable opioid related treatment admissions to healthcare facilities. This should assist in reducing medical care expenses within the United States.

Upon review of available analytics, I have determine that the efforts of state legislators to reduce opioid abuse within the United States during the last nineteen years have at best been a deterrent but have not been effective in ending the opioid crisis. In contrast to policy expectations, non-patient specific prescription laws resulted in significant increases in both opioid related mortality and treatment admissions, but third-party prescription and Good Samaritan laws did not have any significant effect on opioid outcomes. In addition, subsample analysis did not reveal significant variation in the impact of state naloxone access policies

between high opioid risk subgroups and the full sample population. It should be noted that issues of moral hazard and policy endogeneity indicate that these results may not be reliable.

REFERENCES

Bao, Yuhua, Yijun Pan, Aryn Taylor, Sharmini Radakrishnan, Feijun Luo, Harold Alan Pincus, and Bruce R. Schackman. "Prescription drug monitoring programs are associated with sustained reductions in opioid prescribing by physicians." Health Affairs 35, no. 6 (2016): 1045-1051.

Clark, Angela K., Christine M. Wilder, and Erin L. Winstanley. "A systematic review of community opioid overdose prevention and naloxone distribution programs." Journal of addiction medicine 8, no. 3 (2014): 153-163.

Drug Overdose Deaths in the United States, 1999–2017. (2018, November 29). Retrieved March 1, 2019, from https://www.cdc.gov/nchs/products/databriefs/db329.htm#fig2

Evans, William N., Ethan Lieber, and Patrick Power. How the reformulation of OxyContin ignited the heroin epidemic. No. w24475. National Bureau of Economic Research, 2018.

Haegerich, Tamara M., Leonard J. Paulozzi, Brian J. Manns, and Christopher M. Jones. "What we know, and don't know, about the impact of state policy and systems-level interventions on prescription drug overdose." Drug and alcohol dependence 145 (2014): 34-47.

Hauswirth, B. (2018, December 03). Missouri prescription drug monitoring program legislation. Retrieved March 1, 2019, from https://www.missourinet.com/2018/12/02/missouri-prescription-drug-monitoring-program-legislation-to-be-filed-monday-by-rehder-audio/

Hollingsworth, Alex, Christopher J. Ruhm, and Kosali Simon. "Macroeconomic conditions and opioid abuse." Journal of health economics 56 (2017): 222-233.

Ho, J. Y. (2017). The contribution of drug overdose to educational gradients in life expectancy in the United States, 1992–2011. Demography, 54(3), 1175-1202.

Johnson, Hal, Leonard Paulozzi, Christina Porucznik, Karin Mack, and Blake Herter. "Decline in drug overdose deaths after state policy changes-Florida, 2010-2012." MMWR. Morbidity and mortality weekly report 63, no. 26 (2014): 569-574.

Kerensky, Todd, and Alexander Y. Walley. "Opioid overdose prevention and naloxone rescue kits: what we know and what we don't know." Addiction science & clinical practice 12, no. 1 (2017): 4.https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5219773/

Kosten, Thomas R., and Tony P. George. "The neurobiology of opioid dependence: implications for treatment." *Science & Practice Perspectives* 1, no. 1 (2002): 13. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC2851054/

"Legal Interventions to Reduce Overdose Mortality: Naloxone Access and Overdose Good Samaritan Laws." *The Network of Public Health Law*. July 17, 2017. Accessed September 30, 2018. https://www.networkforphl.org/_asset/qz5pvn/legal-interventions-to-reduce-overdose.pdf

Ling, Walter, Leslie Amass, Steve Shoptaw, Jeffrey J. Annon, Maureen Hillhouse, Dean Babcock, Greg Brigham et al. "A multi-center randomized trial of buprenorphine–naloxone versus clonidine for opioid, detoxification: findings from the National Institute on Drug Abuse Clinical Trials Network." Addiction 100, no. 8 (2005): 1090-1100.

"Naloxone Access Laws Tool - Samhsa.gov." *SAMHSA*. January 20, 2018. Accessed September 22, 2018. https://www.samhsa.gov/capt/sites/default/files/resources/naloxone-access-laws-tool.pdf.

"Naloxone Overdose Prevention Laws." Legal Science, July 1, 2017. Accessed September 22, 2018.

National Center for Health Statistics. Multiple cause-of-death data, 1999–2015. CDC WONDER online database. 2017.

"N-SSATS." SAMHSA, 2017. Accessed September 22, 2018.

Popovici, Ioana, Johanna Catherine Maclean, Bushra Hijazi, and Sharmini Radakrishnan. "The effect of state laws designed to prevent nonmedical prescription opioid use on overdose deaths and treatment." Health economics 27, no. 2 (2018): 294-305.

Powell, David, Rosalie Liccardo Pacula, and Erin Taylor. How increasing medical access to opioids contributes to the opioid epidemic: evidence from medicare part d. No. w21072. National Bureau of Economic Research, 2016.

Powell, David, Rosalie Liccardo Pacula, and Mireille Jacobson. "Do medical marijuana laws reduce addictions and deaths related to pain killers?" Journal of health economics 58 (2018): 29-42.

"Public Policy Statement on the Use of Naloxone for the Prevention of Opioid Overdose Deaths." *ASAM*. 2017. Accessed September 30, 2018. https://www.asam.org/docs/default-source/public-policy-statements/use-of-naloxone-for-the-prevention-of-opioid-overdose-deaths-final.pdf

Rees, Daniel I., Joseph J. Sabia, Laura M. Argys, Joshua Latshaw, and Dhaval Dave. With a little help from my friends: The effects of naloxone access and good samaritan laws on opioid related deaths. No. w23171. National Bureau of Economic Research, 2017.

Reifler, Liza M., Danna Droz, J. Elise Bailey, Sidney H. Schnoll, Reginald Fant, Richard C. Dart, and Becki Bucher Bartelson. "Do prescription monitoring programs impact state trends in opioid abuse/misuse?." Pain Medicine 13, no. 3 (2012): 434-442.

Scholl L, Seth P, Kariisa M, Wilson N, Baldwin G. Drug and Opioid-Involved Overdose Deaths – United States, 2013-2017. Morb Mortal Wkly Rep. ePub: 21 December 2018

Strang J, Manning V, Mayet S, et al. Overdose training and take-home naloxone for opiate users: prospective cohort study of impact on knowledge and attitudes and subsequent management of overdoses. Addiction 2008; 103:1648–1657.

2019 Poverty Guidelines. (2019, January 11). Retrieved March 1, 2019, from https://aspe.hhs.gov/2019-poverty-guidelines

Wide-ranging online data for epidemiologic research (WONDER). Atlanta, GA: CDC, National Center for Health Statistics; 2016. Accessed March 1, 2019.

Wolfers, Justin. 2006. "Did Unilateral Divorce Laws Raise Divorce Rates? A Reconciliation and New Results." American Economic Review 96 (5):1802-1820.

Table 1. **Data Summary**

Variable	Obs	Mean	Std. Dev.	Min	Max
mortality	2,251,323	7.925	5.484	0.514	45.874
admissions	1,876,978	115.224	103.609	0.119	715.208
year	2,269,061	200920.200%	4.951	1999	2017
npl	2,269,061	18.000%	0.384	0	1
tpl	2,269,061	22.401%	0.417	0	1
gsl	2,269,061	19.365%	0.395	0	1
pdmp	2,212,447	68.717%	0.464	0	1
pmcl	2,269,061	7.904%	0.270	0	1
age_18to24	2,269,061	6.435%	0.245	0	1
age_25to34	2,269,061	17.460%	0.380	0	1
age_35to44	2,269,061	22.709%	0.419	0	1
age_45to54	2,269,061	27.108%	0.445	0	1
age_55to64	2,269,061	26.288%	0.440	0	1
male	2,269,061	47.061%	0.499	0	1
white	2,269,061	81.869%	0.385	0	1
black	2,269,061	6.496%	0.246	0	1
other	2,269,061	11.635%	0.321	0	1
less_than_high_school	2,269,061	11.635%	0.321	0	1
high_school	2,269,061	23.156%	0.422	0	1
some_college	2,269,061	28.025%	0.449	0	1
bachelor_and_above	2,269,061	44.588%	0.497	0	1
not_in_labor_force	2,269,061	17.095%	0.376	0	1
employed	2,269,061	77.861%	0.415	0	1
not_employed	2,269,061	5.044%	0.219	0	1
less_than_25k	2,269,061	17.161%	0.377	0	1
less_than_50k	2,269,061	24.758%	0.432	0	1
less_than_75k	2,269,061	19.222%	0.394	0	1
greater_than_75k	2,269,061	38.859%	0.487	0	1
married	2,269,061	59.314%	0.491	0	1
divorced_widowed_separated	2,269,061	19.174%	0.394	0	1
never_married	2,269,061	21.512%	0.411	0	1
nonsmoker	2,269,061	78.383%	0.412	0	1
smoker	2,269,061	21.617%	0.412	0	1
binge_drink	2,269,061	10.928%	0.312	0	1

Table 2. Mortality Regression – Full Sample

	Column 1	Column 2	Column 3	Column 4	Column 5
VARIABLES	mortality	mortality	mortality	mortality	mortality
npl	1.386	1.386	1.869**		
	(1.219)	(1.219)	(0.884)		
tpl	0.782	0.782		1.321*	
	(0.889)	(0.889)		(0.660)	
gsl	0.261	0.261			0.948
	(1.207)	(1.207)			(0.952)
pdmp	-0.789	-0.789	-0.824	-0.834	-0.833
	(0.827)	(0.827)	(0.845)	(0.846)	(0.854)
pmcl	1.617	1.617	1.612	1.616	1.673
	(1.810)	(1.810)	(1.820)	(1.805)	(1.811)
age_18to24	-0.062	-0.062	-0.062	-0.062	-0.063
	(0.039)	(0.040)	(0.041)	(0.039)	(0.040)
age_25to34	-0.103***	-0.103***	-0.104***	-0.103***	-0.105***
	(0.035)	(0.035)	(0.036)	(0.035)	(0.036)
age_35to44	-0.104***	-0.103***	-0.105***	-0.105***	-0.105***
	(0.027)	(0.027)	(0.027)	(0.026)	(0.027)
age_45to54	-0.030*	-0.029*	-0.030*	-0.029*	-0.026*
	(0.015)	(0.015)	(0.016)	(0.016)	(0.015)
male	-0.015*	-0.014*	-0.014	-0.014	-0.014*
	(0.008)	(0.008)	(0.009)	(0.009)	(0.008)
black	0.007	0.006	0.006	0.007	0.014
	(0.061)	(0.061)	(0.065)	(0.064)	(0.063)
other	-0.057	-0.056	-0.056	-0.056	-0.052
	(0.037)	(0.038)	(0.037)	(0.038)	(0.038)
high_school	-0.004	-0.004	-0.004	-0.003	-0.003
	(0.017)	(0.017)	(0.017)	(0.018)	(0.018)
some_college	0.027	0.028	0.029	0.028	0.029
	(0.019)	(0.020)	(0.019)	(0.019)	(0.020)
bachelor_and_above	0.032	0.032	0.034	0.032	0.036
	(0.029)	(0.030)	(0.029)	(0.030)	(0.031)
employed	0.010	0.010	0.011	0.010	0.011
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
not_employed	-0.004	-0.005	-0.004	-0.007	-0.007
	(0.019)	(0.018)	(0.018)	(0.020)	(0.019)
less_than_25k	0.066*	0.066*	0.064*	0.071**	0.069**
	(0.034)	(0.033)	(0.034)	(0.034)	(0.034)
less_than_50k	0.039	0.039	0.038	0.043*	0.041*
	(0.024)	(0.024)	(0.023)	(0.024)	(0.024)
less_than_75k	0.014	0.014	0.014	0.015	0.014
	(0.019)	(0.019)	(0.018)	(0.018)	(0.019)
divorced_widowed_separated	-0.021**	-0.021**	-0.020**	-0.023**	-0.022**
	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)
never_married	-0.044**	-0.044**	-0.043**	-0.047***	-0.045**
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
smoker	-0.002		-0.002	-0.002	-0.003
	(0.010)		(0.010)	(0.010)	(0.009)
binge_drink	0.008		0.009	0.010	0.009
	(0.008)		(0.008)	(0.008)	(0.008)
Observations	2194709	2194709	2194709	2194709	2194709
R-squared	0.734	0.734	0.732	0.731	0.730

Table 3. Admissions Regression – Full Sample

	Column 1	Column 2	Column 3	Column 4	Column 5
VARIABLES	admissions	admissions	admissions	admissions	admissions
	all	no drugs	npl only	tpl only	gsl only
npl	33.137**	33.137**	29.246*		
	(14.682)	(14.682)	(15.096)		
tpl	5.166	5.166		7.524	
	(13.463)	(13.463)		(13.173)	
gsl	-16.042	-16.041			-7.715
	(15.262)	(15.262)			(14.409)
pdmp	12.649	12.650	13.293	12.616	11.958
	(12.213)	(12.214)	(12.654)	(12.673)	(12.569)
pmcl	-26.955*	-26.957*	-26.122*	-25.449*	-25.618*
	(13.771)	(13.772)	(13.592)	(13.704)	(13.847)
age_18to24	-1.221**	-1.204**	-1.242**	-1.278**	-1.275**
	(0.488)	(0.491)	(0.502)	(0.524)	(0.515)
age_25to34	-1.228***	-1.196***	-1.240***	-1.250***	-1.257***
	(0.396)	(0.398)	(0.409)	(0.418)	(0.413)
age_35to44	-1.167***	-1.143***	-1.144***	-1.164***	-1.192***
	(0.330)	(0.328)	(0.332)	(0.338)	(0.344)
age_45to54	-0.458**	-0.441**	-0.421**	-0.399*	-0.412*
	(0.203)	(0.202)	(0.208)	(0.213)	(0.208)
male	-0.265	-0.255	-0.275	-0.271	-0.263
	(0.176)	(0.174)	(0.171)	(0.173)	(0.178)
black	0.489	0.477	0.580	0.629	0.620
	(0.671)	(0.672)	(0.758)	(0.770)	(0.717)
other	-0.447	-0.456	-0.431	-0.423	-0.398
	(0.499)	(0.503)	(0.497)	(0.512)	(0.499)
high_school	-0.095	-0.125	-0.087	-0.067	-0.071
	(0.249)	(0.257)	(0.249)	(0.253)	(0.249)
some_college	0.058	0.012	0.052	0.041	0.052
	(0.264)	(0.282)	(0.260)	(0.261)	(0.270)
bachelor_and_above	0.133	0.058	0.150	0.137	0.161
	(0.375)	(0.407)	(0.395)	(0.393)	(0.405)
employed	0.157	0.156	0.158	0.150	0.166
	(0.178)	(0.178)	(0.174)	(0.174)	(0.173)
not_employed	0.039	0.059	0.046	-0.010	-0.014
	(0.222)	(0.226)	(0.220)	(0.229)	(0.227)
less_than_25k	-0.558	-0.520	-0.541	-0.475	-0.522
	(0.486)	(0.474)	(0.526)	(0.522)	(0.531)
less_than_50k	-0.303	-0.286	-0.299	-0.232	-0.249
	(0.336)	(0.332)	(0.350)	(0.358)	(0.356)
less_than_75k	-0.240	-0.234	-0.243	-0.230	-0.241
	(0.178)	(0.179)	(0.181)	(0.178)	(0.180)
divorced_widowed_separated	0.024	0.052	0.016	-0.025	-0.015
	(0.204)	(0.219)	(0.212)	(0.219)	(0.217)
never_married	-0.052	-0.033	-0.040	-0.093	-0.083
	(0.241)	(0.243)	(0.247)	(0.258)	(0.253)
smoker	0.258		0.234	0.241	0.258
	(0.191)		(0.198)	(0.202)	(0.192)
binge_drink	0.153		0.129	0.145	0.160
	(0.130)		(0.128)	(0.125)	(0.127)
Constant	103.666***	103.765***	102.452***	103.261***	103.971***
	(9.723)	(9.688)	(9.683)	(9.580)	(9.758)
Observations	1827853	1827853	1827853	1827853	1827853
R-squared	0.832	0.832	0.831	0.829	0.829

Table 4. Mortality Regression – Age Subsample Analysis

	Column 1	Column 2	Column 3	Column 4	Column 5	Column 6
VARIABLES	mortality	mortality	mortality	mortality	mortality	mortality
	age 35-44	age 45-54	age 35-44	age 45-54	age 35-44	age 45-54
npl	1.869**	1.869**				
	(0.884)	(0.884)				
tpl			1.321*	1.321*		
			(0.660)	(0.660)		
gsl					0.948	0.949
					(0.953)	(0.953)
Observations	2194709	2194709	2194709	2194709	2194709	2194709
R-squared	0.732	0.732	0.731	0.731	0.730	0.730
Robust standard errors in parentheses						
*** p<0.01, ** p<0.05, * p<0.1						

Notes: Only results for policy variables of interest are given. Complete results can be accessed upon request.

Table 5. Mortality Regression – Annual Household Income and Education Level Subsample Analysis

	Column 1	Column 2	Column 3	Column 4	Column 5	Column 6
VARIABLES	mortality	mortality	mortality	mortality	mortality	mortality
	Annual Household Income <$25k	Annual Household Income <$25k	Annual Household Income <$25k	Education <bachelors	Education <bachelors	Education <bachelors
npl	1.869**			1.869**		
	(0.884)			(0.884)		
tpl		1.321*			1.321*	
		(0.660)			(0.660)	
gsl			0.949			0.948
			(0.953)			(0.952)
Observations	2194709	2194709	2194709	2194709	2194709	2194709
R-squared	0.732	0.731	0.730	0.732	0.731	0.730
Robust standard errors in parentheses						
*** p<0.01, ** p<0.05, * p<0.1						

Notes: Only results for policy variables of interest are given. Complete results can be accessed upon request.

Table 6. Admissions Regression – Age Subsample Analysis

	Column 1	Column 2	Column 3	Column 4	Column 5	Column 6
VARIABLES	admissions	admissions	admissions	admissions	admissions	admissions
	age 35-44	age 45-54	age 35-44	age 45-54	age 35-44	age 45-54
npl	29.250*	29.252*				
	(15.099)	(15.099)				
tpl			7.527	7.529		
			(13.174)	(13.174)		
gsl					-7.716	-7.712
					(14.412)	(14.413)
Observations	1827853	1827853	1827853	1827853	1827853	1827853
R-squared	0.831	0.831	0.829	0.829	0.829	0.829
Robust standard errors in parentheses						
*** p<0.01, ** p<0.05, * p<0.1						

Notes: Only results for policy variables of interest are given. Complete results can be accessed upon request.

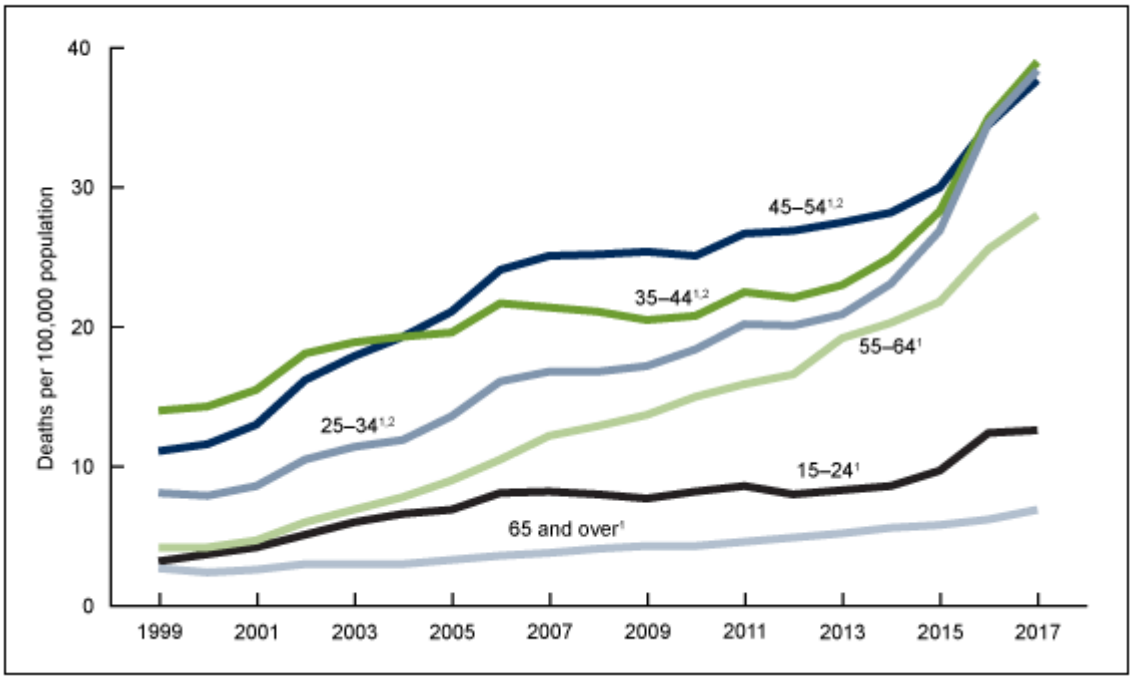
Table 7. Admissions Regression – Annual Household Income and Education Level Subsample Analysis

	Column 1	Column 2	Column 3	Column 4	Column 5	Column 6
VARIABLES	admissions	admissions	admissions	admissions	admissions	admissions
	Annual Houeshold Income <$25k	Annual Houeshold Income <$25k	Annual Houeshold Income <$25k	Education <bachelors	Education <bachelors	Education <bachelors
npl	29.245*			29.246*		
	(15.097)			(15.097)		
tpl		7.525			7.525	
		(13.173)			(13.173)	
gsl			-7.715			-7.715
			(14.409)			(14.409)
Observations	1827853	1827853	1827853	1827853	1827853	1827853
R-squared	0.831	0.829	0.829	0.831	0.829	0.829
Robust standard errors in parentheses						
*** p<0.01, ** p<0.05, * p<0.1						

Notes: Only results for policy variables of interest are given. Complete results can be accessed upon request.

APPENDIX 1

Figure 1. Drug overdose death rates, by selected age group: United States, 1999-2017



Notes: The results show increasing trends of drug overdose death rates from 1999 through 2017. 2017 rates were significantly higher for age groups 25-34, 35-44, and 45-54 than for age groups15-24, 55-64, and 65 and over ($p < 0.05$).
Source: Data is from the NCHS, National Vital Statistics System, Mortality (Drug, 2018).