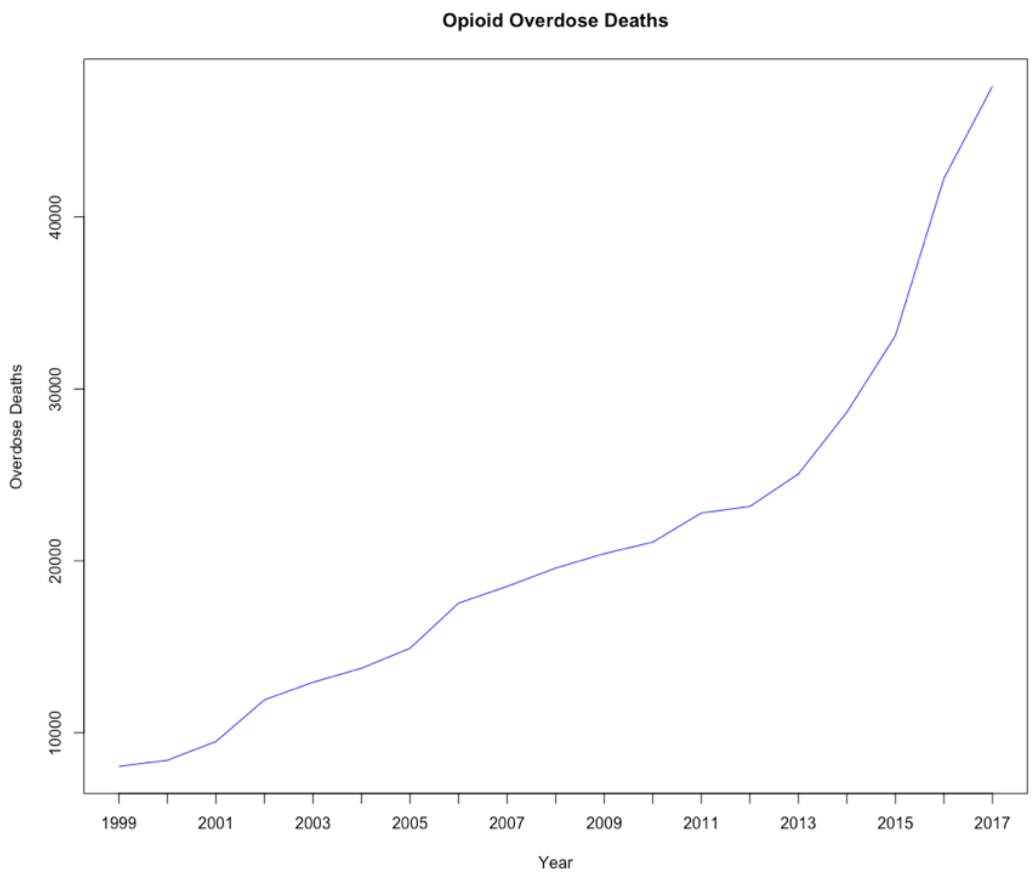
I. Introduction

The United States is currently in the midst of a public health crisis. For the past two decades, the growing opioid crisis, characterized by a skyrocketing level of overdose deaths, has spread throughout the country. In 2017 alone, 47,600 people in the United States died from an opioid overdose, making accidental overdose more deadly than traffic fatalities or gun deaths (National Safety Council, 2017).

Given its impact on the American public, the opioid crisis has captivated the national dialogue in the United States. In 2016, President Donald Trump declared the opioid crisis to be not only a "national public health emergency," but the "worst drug crisis in American history" (Allen and Kelly, 2019). Opioid overdose deaths indeed have increased markedly in the United States over the last two decades—by nearly 491% between 1999 and 2017, as demonstrated in **Figure 1** (CDC Wonder, 2018). Over this same period, opioid prescribing by physicians and other medical providers has also increased rather dramatically. Beginning in the mid-1990s, with the introduction of prescription opioids such as OxyContin to the mass market, pain clinics and providers started to embrace the use of these drugs, propelling opioids to the forefront of the medical community as a "safe, salutary and more humane alternative" in palliative care (Portenoy and Foley, 1986). From 1990 to 2015, opioid prescribing increased by a staggering 874% (Pain & Policy Studies Group).

Figure 1



The mainstream "Standard Narrative" for the origin of the opioid crisis, most notably promulgated by the Centers for Disease Control and Prevention (CDC), blames this increase in prescribing for the rise in opioid overdose deaths.

This viewpoint holds that,

> [i]n the late 1990s, pharmaceutical companies reassured the medical community that patients would not become addicted to prescription opioid pain relievers, and healthcare providers began to prescribe them at greater rates. This subsequently led to widespread diversion and misuse of these medications before it became clear that these medications could indeed be highly addictive. Opioid overdose rates began to increase (CDC, 2019).

Thus, public policy geared towards reducing the rising number of deaths has looked to curb the high level of opioids prescribed by physicians. According to the CDC, "[r]educing exposure to prescription opioids, for situations where the risks of opioids outweigh the benefits, is a crucial part of prevention" (CDC, 2014).

One of the policies which the CDC recommends to combat overprescribing is the Prescription Drug Monitoring Program (PDMP). PDMPs are "state-run databases that track prescriptions for painkillers and...make data available in real-time" (CDC, 2014). The goal of these policies is to limit "doctor shopping," or the practice of when those seeking opioids visit several doctors in order to receive multiple prescriptions (Griggs et al., 2015).

However, while PDMPs may intend to curb opioid overdose deaths by limiting the quantity of opioids prescribed to patients, it is in fact plausible that the enactment of PDMPs only makes matters worse in terms of deaths. Since 2014, the majority of opioid overdose deaths have not come from prescription opioids such as OxyContin, but from illicit street opioids such as heroin and fentanyl (CDC Wonder, 2018). PDMPs, which only monitor prescription opioids, do nothing to directly curb the use of such illicit drugs. Furthermore, PDMPs may actually exacerbate illicit opioid overdose deaths by creating a substitution to drugs acquired on the black market. If users are cut off from legal opioids due to restrictions such as PDMPs, yet still have a demand for these drugs, often they will turn to the black market in order to satisfy this demand by purchasing illicit drugs like heroin. In turn, the risks of opioid use are amplified when drugs are acquired illegally due to the lack of quality control and consumer information regarding the contents and purity of a substance acquired via underground markets (Miron and Zwiebel, 1995).

Given the dire state of the opioid crisis, this thesis seeks to provide a timely analysis of the effectiveness of PDMPs. In a period where opioid overdose deaths are continuously skyrocketing in the United States, it is necessary for the policymaking community to understand the consequences of its interventions aimed at addressing overdose deaths. If PDMPs are in fact contributing to the rising level of opioid overdose deaths in the United States or creating the aforementioned substitution to illicit opioids, then their effectiveness as a legitimate policy tool to combat the overdose crisis is called into question.

In an effort to evaluate the effectiveness of PDMPs at meeting their desired goal of reducing overdose deaths, I examine the relationships between PDMPs and prescribing, and PDMPs and opioid overdose deaths. I also analyze whether PDMPs are associated with any unintended spillovers into crime rates, which may occur as an unintended consequence of changes in prescribing levels after PDMP implementation. Through running several linear regression models, I find that while PDMPs which mandate prescriber participation do in fact have a statistically significant, negative relationship with opioid prescribing, I find no evidence suggesting that the implementation of PDMPs is associated with a decrease in total opioid overdose deaths.

Upon further examination of this relationship, I find that though PDMPs are associated with a reduction in deaths attributed to natural and semi-synthetic opioids—those usually received through a physician's prescriptions—they are also associated with an increase in heroin deaths, indicating that substitution to illicit opioids may arise in the wake of prescribing restrictions. This provides evidence for the claim that PDMPs are not successful in meeting their goal of reducing total opioid overdose deaths because of this unintended consequence of increased overdose deaths on illicit opioids such as heroin, which mitigates any gains achieved by reducing prescription opioid overdose deaths. Lastly, I find no evidence that PDMPs have a spillover effect on crime rates.

II. Background on PDMPs

PDMPs have been used in the United States since the early twentieth century. Prior to 1914, natural opiates—the predecessor to the modern synthetic or semi-synthetic "opioid"—were unregulated by the federal government and widely available for purchase without prescription in the United States (Jones et al., 2018). Use among the American public was quite commonplace. According to one article published in *The New York Times*, one in every four-hundred United States citizens had some type of opiate addiction by 1911 (Marshall, 1911). In response to the rising level of opiate use in the United States, Congress passed the Harrison Narcotics Tax Act in 1914, the first federal statute regulating the production and sale of opiates. Under this law, physicians were restricted from prescribing opiates to addiction patients and all proprietors of opium products needed to be registered with the federal government, creating the ancestor to the modern PDMP database.

One reason cited as a motivation for the Harrison Act was "the careless prescribing of these drugs by physicians" (Terry, 1915). In an effort to further combat overprescribing, states slowly began to develop their own monitoring programs, the first of which was created in New York in 1918.

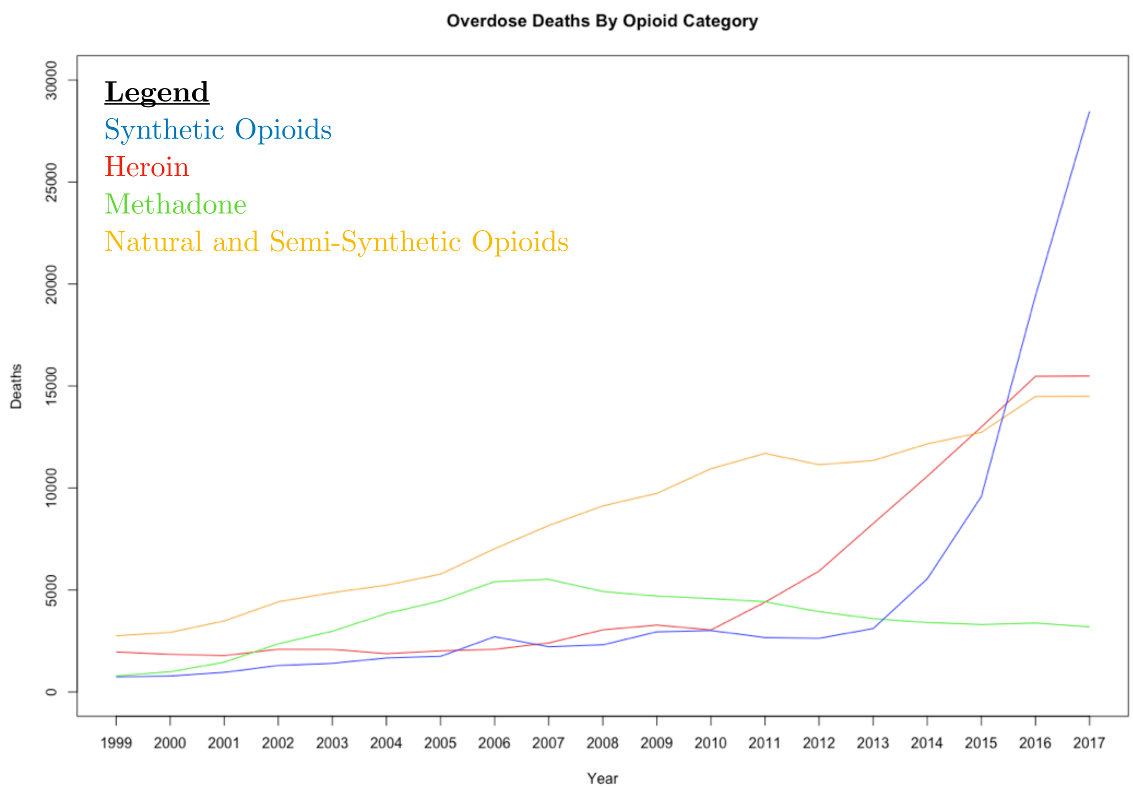
However, these early PDMPs were rather slow in their collection times and used inefficient paper reports to monitor the prescription history of patients (PDMP TTAC, 2018). According to one study, the programs developed throughout the mid-twentieth century were rather ineffective, as "[p]rescribers were required to report to databases within 30 days, too long a time to reasonably be useful in preventing 'doctor shopping' or over-prescribing" (Stolz, 2016).

Given the weakness of these early PDMPs, few states adopted any type of monitoring program over the course of the first half of the twentieth century. However, the proliferation of PDMPs was greatly enabled by the ruling of *Whalen v. Roe* in 1977, a case which upheld the constitutionality of New York's PDMP under the broad police power given to the states by the 10th Amendment. The plaintiffs of this case argued that the monitoring program constituted an invasion of patient privacy, due to its collection and storing of prescribing records. Writing for the majority, Justice John Paul Stevens held that, "[n]either the immediate nor the threatened impact of the patient identification requirement on either the reputation or the independence of patients...suffices to constitute an invasion of any right or liberty protected by the Fourteenth Amendment" (Whalen v. Roe, 1977). With the constitutionality of patient prescription monitoring upheld, states were able to pursue data collection on prescribing history more thoroughly. Empowered by this ruling, many more states began to operate some form of a PDMP.

By 1990, states such as Oklahoma and Nevada began to adopt electronic reporting systems, greatly expanding the capabilities of these programs. These improvements "reduced operational costs" and increased the accuracy of the databases, leading other states to consider them as a viable means for monitoring opioid prescribing (PDMP TTAC, 2018). In 2003, Congress further increased funding for state PDMPs through the Harold Rogers Prescription Drug Monitoring Programs Grant, a competitive federal grant program which allows states to receive federal funding to "enhance the capacity of regulatory and law enforcement agencies and public health officials to collect and analyze controlled substance prescription data...through a centralized database administered by an authorized state agency" (Bureau of Justice Assistance, 2016).

At the time in 2003, the PDMP seemed to be an effective way to combat opioid overdose deaths. The CDC divides the modern opioid crisis into three distinct waves, the first beginning "in the 1990s, with overdose deaths involving prescription opioids (natural and semi-synthetic opioids and methadone) increasing since at least 1999" (CDC, 2018). Given that the majority of opioid deaths in 2003 were due to prescription drugs, the PDMP's intended purpose of limiting opioid prescribing seemed logical. However, as demonstrated by **Figure 2,** by 2010 the second wave of the opioid crisis came on "with rapid increases in overdose deaths involving heroin," and not prescription opioids (CDC, 2018). Finally, the third wave of the crisis took hold beginning in 2013, as synthetic opioids such as fentanyl drove the most recent spike in opioid overdose deaths.

Figure 2



Since 2014, the majority of opioid deaths in the United States have not been due to overdoses from prescription opioids—those monitored by PDMPs—but from illicit drugs like heroin and fentanyl. Therefore, the PDMP does not directly address ways by which policy can curb the types of overdoses that are most prevalent in the present day. Additionally, by limiting access to legally prescribed opioids, PDMPs may actually be driving people towards these illicit substances like heroin and fentanyl, as users are cut off from legal channels of prescribing and therefore must turn to black markets to acquire opioids illegally (Miron et al., 2019).

Yet, due to increased access to funding and resources under the Harold Rogers Program, by 2016, every state, with the exception of Missouri, had enacted some form of a PDMP. States, however, vary on the extent to which participation in these databases are mandatory and on what types of drugs are monitored. All states with operational PDMPs monitor at least Schedule II-IV opioids, and the majority of states also monitor prescriptions for Schedule V opioid products, such as codeine cough syrup. PDMPs are administered by state government agencies and compile accessible information on prescribing history which is entered into the database by health care providers. These systems are updated on a daily or weekly basis, depending on the state (PDMP TTAC).

The PDMP is now widely regarded as a popular policy mechanism which states can use to combat the opioid crisis. Given the crisis' wide-reaching effect across the United States, policies such as this aimed at curbing the opioid crisis are now considered a priority by politicians across the political spectrum. Legislators with ideologies as differing as Bernie Sanders and Ben Sasse have rallied in unison in support of legislation aimed at lowering overdose deaths. In a time of unprecedented political divide and gridlock, it is exceptional for any policy to garner such universal support.

For example, in October of 2018, the United States Senate passed the Substance Use-Disorder Prevention that Promotes Opioid Recovery and Treatment (SUPPORT) for Patients and Communities Act, a bill which strengthened state PDMPs by encouraging interstate sharing of data and mandated PDMP use for all Medicaid providers, by a margin of 98-1—indicating the unified nature of mainstream political thought surrounding this issue. Though all PDMPs are administered by the states, this legislation enhanced funding for state PDMPs and created a mechanism by which a patient's prescription history could be accessed across state lines (Musumeci and Tolbert, 2018).

The dire magnitude of the opioid crisis has created an imperative for legislators, forcing them to act quickly in order to stem the rising level of overdose deaths. As Texas Senator Ted Cruz stated in 2018 in support of the SUPPORT for Patients and Communities Act, "[t]oo many lives have been lost to the opioid crisis, and today we take a stand for all Americans. I am proud of Congress' actions today to take a stand in efforts to save millions from the ravages of drug addiction" (Cruz, 2018). It is this sense of urgency—legislating in response to tens of thousands of overdose deaths every year—that has created universal support for these interventions, with little, if any, public debate or criticism of them. However, the academic literature surveying PDMPs is far more divided than the popular support for this policy suggests.

III. Literature Review

The nearly universal adoption of PDMPs over the past two decades is a direct response to the rising number of opioid deaths in the United States (Haffajee et al., 2015). Since 1999, opioid overdose deaths have risen by nearly 500%, leading the public health community to brand America's battle with opioids a "crisis" (Hedegaard et. al, 2017).

In times of crisis, governments have a tendency to expand in order to create new programs aimed at mitigating said crisis. There is a rich literature in the political science discipline conceptualizing the ways in which states respond to crises through policy. According to Redford and Powell (2016), "[c]risis, or the perception thereof, plays a crucial role in the dynamics of intervention." Higgs (1987) argues that times of crisis allow governments the political capital to undertake significant policy interventions in order to address the pressing issue at hand and that these interventions substantially facilitate the growth of government over time. As such, it appears that the opioid crisis facing the United States has provided governments at the state and federal level the opportunity to further intervene in restricting access to prescription drugs.

Furthermore, the dire nature of crises tends to force legislators to act quickly and resolutely in order to do anything which may stem the crisis—even when their chosen policy interventions may not be widely supported by evidence. As Aitken and Hoover (1960) explain, in times of crisis, "there is likely to be an insistent demand for emergency action of some sort and relatively little consideration of what the permanent effect will be." Thus, facing the need for an immediate response, governments in times of crisis tend to act less deliberately, without carefully weighing the consequences of intervention before acting.

A branch of this literature also specifically focuses on the impetus for government action against the use of controlled substances. Mark Thornton (1991b) hypothesizes that, "[t]he demand for interventionist policies such as prohibition arises from the perception that the market process has caused an inefficient outcome or that the market will not correct inefficiencies." Under this interpretation, absent PDMPs and other restrictions on prescribing, the government believes that the free, unregulated exchange for prescription opioids between patients and physicians would result in a sub-optimal outcome, namely the overprescribing of opioids. Thus, these policies are intended to correct for this and work towards bringing opioid prescribing down to the desired level.

In the context of the opioid crisis, this theory of immediate action may help explain why PDMPs have been so widely adopted, even as there is an ongoing debate in the relevant literature regarding the effectiveness of the PDMP and the unintended consequences associated with its adoption.

Two Competing Narratives to Explain the Opioid Crisis

The causes of the recent spike in opioid deaths in the United States are generally explained in the literature by two competing narratives. On one hand, the "Standard Narrative" holds that the opioid crisis was primarily caused by the overprescribing of prescription opioids and that as opioid prescribing rates increased, more people began to get addicted to these drugs, leading to more accidental overdoses (See, for instance, Van Zee, 2009). The PDMP is seen by proponents of the Standard Narrative as a policy that states can employ to reduce opioid prescribing, and in turn, lower overdose deaths because fewer people will be taking these drugs.

Competing with this mainstream narrative that a reduction in opioid prescribing should yield a decrease in overdose deaths is an alternative hypothesis which holds that restrictions which cause a decrease in prescribing should be associated with an increase in socially undesirable consequence such as overdose deaths (Miron et al, 2019). This "Alternative

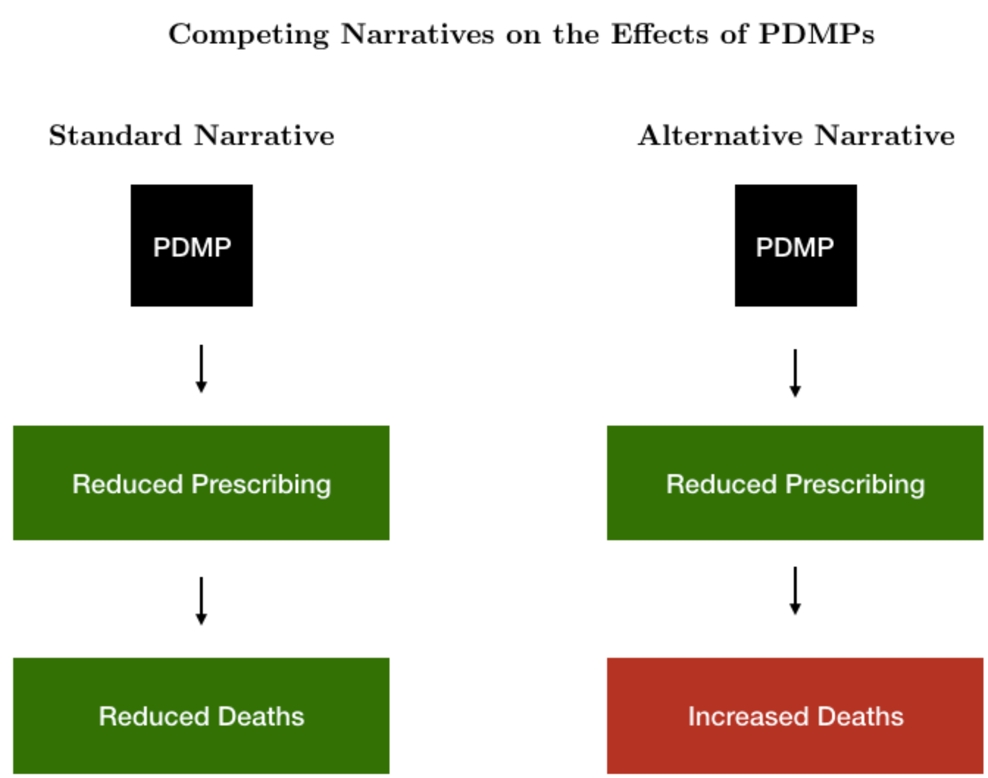
Narrative" does not contest that PDMPs are effective in reducing prescribing but posits that because legal access to opioids is reduced, an increase in illicit opioid deaths occurs.

According to the Alternative Narrative, the recent spike in overdose deaths is best explained by the hypothesis that under restrictions on prescribing, people with a demand for opioids who are cut off from legal channels of access will turn to the black market to meet this demand. In turn, the drugs acquired on the black market, such as heroin and fentanyl, are far more dangerous than those achieved through legal channels due to heightened potency and a lack of consumer information about the true contents of the substance, leading to more accidental overdoses (Miron and Zwiebel, 1995). Thus, any reductions made by a decrease in prescription drug overdoses should be mitigated by an increase in overdoses on these more dangerous illicit drugs.

The purpose of this thesis is not necessarily to identify the underlying causes of the opioid crisis. Instead, I plan to analyze whether the specific policy intervention of the PDMP has been successful in its goal of reducing overdose deaths or that it in fact has contributed to the crisis by driving users towards the black market, using these narratives as frameworks to explain my findings.

The main conclusions of these hypotheses are summarized in **Figure 3a** below. Both the Standard and Alternative Narratives are based on a wide dialogue of research studying the social effects of drug interdiction. I will now explore more deeply the evidence for each hypothesis as it pertains to the relevant public policy, public health, and economics literature.

Figure 3a



Evidence on the Relationship Between PDMPs and Prescribing Levels

The logic behind the PDMP is based on the assumption that the overprescribing of prescription opioids has led to an increase in overdose deaths (Van Zee, 2009). The Standard Narrative argues that beginning in the mid-1990s with the introduction of OxyContin to the mass market, physicians underestimated the addictive properties of opioid drugs and were too reckless in prescribing them, leading to a rise in opioid addiction among pain patients. In turn, this long-term use of opioids posed a significant risk of overdose for patients (Baldini et al., 2012; Fleming et al., 2007). Thus, by limiting the quantity of opioids prescribed in the first place, the PDMP is intended to work towards mitigating overprescribing and its subsequent effect on overdose deaths.

However, this assumption that increased prescribing is necessarily linked to increased addiction or deaths has been widely challenged in the literature. A recent review of the relevant medical literature finds that only .27% of all chronic pain patients who are prescribed opioids experience dependence (Noble et al., 2010). Several other studies substantiate this claim that opioid use is not associated with high rates of addiction (See, for instance, Cheatle et al, 2018; Han et al, 2017; Adams et al., 2001; Dellemijn, 2001; Cowan et al., 2001). Additionally, the rate of overdose deaths among people taking prescription opioids is extremely low. In a 2010 study, Dunn et al. (2010) find there to be only .06% death rate among patients receiving opioids for chronic non-cancer pain, indicating a rather low risk of death from taking prescription opioids.

Despite the tenuous relationship between long term opioid use and deaths, mainstream public policy assumes this relationship to be more pronounced than the evidence would suggest and looks towards restrictions like the PDMP as a way to address the perceived effect of opioid prescribing on overdoses. However, just because these policies have the intended effect of lowering opioid prescribing, and thus, overdose deaths, this does not necessarily mean that these policies have succeeded in achieving these goals.

The academic literature is inconclusive as to what effect PDMPs have had on this decrease in opioid prescribing. Several studies do in fact find that PDMPs are associated with decreases in prescription opioid consumption in the United States (Kilby, 2015; Paulozzi et al., 2011; Reisman et al., 2009; Simeone and Holland, 2006). However, more recent scholarship qualifies this claim. Using county-level panel data over the years of 2006 and 2015, Ayers and Jalal (2018) find that PDMPs are associated with decreased prescribing, but only "if they obligate doctors to check for patients' history prior to filling out a prescription...." The success of the PDMP in meeting its desired goal of reducing overdose deaths relies on its effectiveness in first reducing prescribing among patients. If there is no relationship between PDMPs which are not mandatory and prescribing, as Ayers and Jalal suggest, then these policies logically cannot have any effect on overdose deaths according to both narratives.

Evidence on the Relationship Between PDMPs and Opioid Overdose Deaths

There is much debate on the effectiveness of state interventions in drug markets in reducing overdose deaths. Consistent with the Alternative Narrative presented above, Miron and Zwiebel (1995) argue that government interventions into drug markets have several unintended consequences, including increased risk of accidental overdose. The authors argue that when governments restrict access to drugs, black markets arise. If demand for drugs, or specifically in this case, opioids, exists, then users will try to access them through illicit means in light of restrictions.

Yet in black markets, the harm of drug use is greatly amplified by a lack of oversight and legal protections. Quality control is greatly inhibited in illegal markets. Consumers are unable to have complete information about the true contents of a substance, for "[g]overnment quality regulation does not exist for illegal commodities, and buyers cannot complain about quality without incriminating themselves" (Miron and Zwiebel, 1995). This lack of information poses a serious risk for illicit opioid users. If restrictions are driving people to illicit markets for opioids, then these substances will be more dangerous than those purchased legally because of the lack of information inherent to drugs purchased on the black market.

This theory of substances becoming more dangerous when sold on a black market was most clearly demonstrated in the United States' experiment with alcohol prohibition in the 1920s. According to Thornton (1991a), "[t]here were few if any production standards during Prohibition, and the potency and quality of products varied greatly, making it difficult to predict their effect." As such, "[t]he death rate from poisoned liquor was appallingly high throughout the country. In 1925 the national toll was 4,154 as compared to 1,064 in 1920," demonstrating the increased risk of substances when acquired on black markets (Coffey, 1976). The illicit nature of opioids under their prohibition in the United States yields a similar relationship between restrictions and quality control. According to the DEA, "[f]entanyl is added to heroin to increase its potency, or be disguised as highly potent heroin. Many users believe that they are purchasing heroin and actually don't know that they are purchasing fentanyl–which often results in overdose deaths" (DEA, 2017). Because users are unable to identify the true contents of their drug, it is virtually impossible for them to titrate the appropriate dose for the substance or know exactly what drug they are consuming. Therefore, if PDMPs are cutting users off from legal channels of opioids and driving them to the black market, one would expect that they are in fact associated with rising levels of illicit opioid deaths.

When evaluating the overall effectiveness of the PDMP, it is necessary to be cognizant of this potential unintended consequence of intervention. Even if PDMPs are found to lower prescription opioid overdose deaths by decreasing the quantity of opioids prescribed, one must also consider their possible relationship with increasing the use of illicitly acquired opioids. If PDMPs are merely diverting users from legal to illicit opioids, while in turn increasing or maintaining the overall death rate, then they should not be viewed as an effective solution to the opioid crisis.

The wider academic evidence on the relationship between PDMPs and overdose deaths is mixed. Kennedy-Hendricks and her colleagues (2016) conclude that the enactment of a PDMP in the state of Florida was associated with decreases in both prescription opioid and heroin overdose deaths, relative to the neighboring state of North Carolina which did not adopt a PDMP at this time—providing evidence for the Standard Narrative's claim that PDMPs help to reduce overdose deaths. It should be noted, however, that heroin deaths still continued to rise in Florida after the adoption of the PDMPs, just at a slower rate than in North Carolina. Furthermore, the findings of this study have been challenged directly by Delcher et al. (2016), who claim that Kennedy-Hendricks' assertions are incorrect and that "heroin-caused deaths may have increased simultaneously" in Florida. Others find that there is no statistically reliable relationship between PDMPs and overdose deaths (Brady et al, 2014; Meara et al, 2016).

In contrast, Brown et al. (2017) find that the PDMP in New York State was associated with not only the leveling off of prescription opioid overdose deaths, but also an increase in heroin deaths. This finding provides evidence for the theoretical claim made by Miron and Zwiebel (1995)—that increased restrictions on legal opioids will cause users to switch to more dangerous illicit opioids like heroin.

Still, many of these aforementioned studies only focus on implementation in one or a few states. This thesis intends to add to the literature by analyzing the results of PDMP implementation in all of the states which have adopted this policy to date and is the first to survey the relationship between PDMPs and overdose deaths over this extended time series of 1999-2017. The inclusion of these more recent years in this thesis makes it an especially useful contribution to this scholarly debate, given the relatively recent adoption of Mandatory PDMPs in the United States and the lack of distinction between mandatory and non-mandatory status in the general literature.

Evidence on the Relationship between PDMPs and Crime

State interventions into drug markets may not only have unintended effects on overdose deaths, but also spillover effects on drug-related crime. Regarding crime, Miron and Zwiebel (1995) state that, "[c]onsiderable evidence indicates a correlation between drug use and the perpetration of income-generating crimes such as theft or prostitution...if crimes are committed to finance drug consumption, prohibition should increase crime by raising prices." Because it is more difficult to access drugs under prohibition than under legal regimes, the supply of that drug decreases, effectively raising its price. In the context of PDMPs, this theory predicts that the enactment of a PDMP should be associated with an increase in income-generating or property crime, as more people resort to theft to fund their, now more expensive, drug habits. Additionally, the Alternative

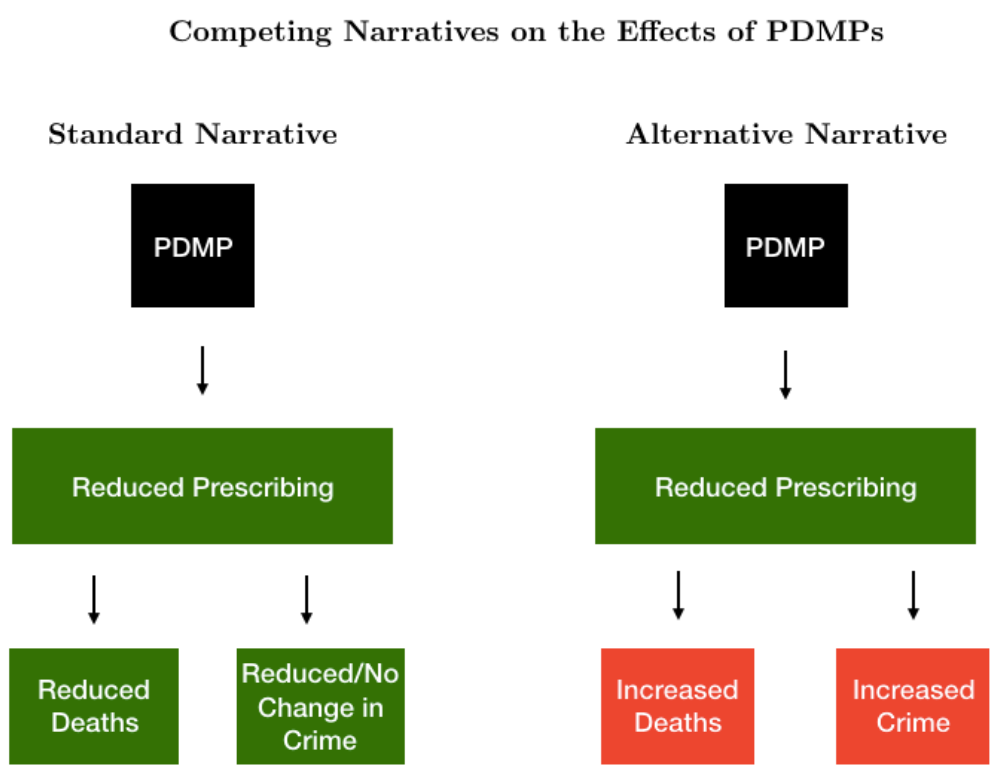
Narrative predicts PDMPs to be associated with an increase in violent crime. Without the protection of courts to enforce transactions in the unregulated black market, parties in illegal drug trade disputes must resort to violence in order to settle disagreements (Miron and Zwiebel, 1995). Thus, as restrictions on prescribing push more people to the black market, violent crime rates should increase.

This relationship between PDMPs and crime is widely studied in the literature. Violent crimes, such as homicide, have been found to be reduced after PDMP implementation (Dave et al., 2018). This finding is at odds with the hypothesis of Miron and Zwiebel, as the evidence suggests that PDMP implementation is associated with a reduction in crime. However, drug-related crimes appear to be positively associated with PDMPs. Mallat (2017) finds that PDMPs increase crime surrounding the "purchase, sale or possession of heroin or illegally obtained prescription opiates" by 87% in the "most opioid dense counties."

These findings are further complicated by an emerging debate in the literature regarding the relative impacts of Mandatory PDMPs and Non-Mandatory PDMPs on crime. As of 2017, 40 states have mandated that prescribers and dispensers of opioids must be registered with or consult the PDMP database before issuing a drug to the patient (PDMP TTAC). This distinction between the relative effectiveness of Mandatory and Non-Mandatory PDMPs is present throughout the literature and seems to significantly impact the outcome of studies observing PDMPs. Much of the literature indicates that Mandatory PDMPs are more effective in reducing socially undesirable outcomes, such as crime, than voluntary ones (Buchmueller and Carey, 2017; Haffajee et al, 2015). One study finds that, "voluntary PDMPs did not significantly affect crime whereas mandatory-access PDMPs have reduced crime by approximately 3.5%" (Dave et al., 2018). However, another finds that Non-Mandatory PDMPs also reduced crime rates, at least between 2007 and 2012 (Deza and Horn, 2017). Additionally, Mallatt (2017) finds no evidence that mandates reduce drug crime more effectively than voluntary programs.

To further summarize these conflicting narratives, I amend **Figure 3a** to add the hypothesized effects of PDMPs on crime consistent with both the Standard and Alternative Narratives, reported below in **Figure 3b**. While the PDMP is not intended to directly target crime, its potential impact on crime rates is certainly relevant to consider when analyzing the full social effects of this policy—especially in evaluating the Alternative Narrative, which argues that the unintended consequences of intervention, such as these potential spillovers on crime, outweigh its benefits. Still, given that the primary policy goal of the PDMP is to reduce deaths, and not necessarily crime, a finding of no relationship between PDMPs and crime should be interpreted as support for the Standard Narrative, as no evidence for unintended negative spillovers as a consequence of PDMP implementation is found.

Figure 3b



Varied Data in the Relevant Literature

Evidently, there is much debate in the academic literature surrounding the efficacy of PDMPs and their effects on several outcomes such as prescribing, deaths, and crime. One reason for this variance may be that the literature is rather inconsistent in the data used to study the effects of PDMPs. Perhaps most troubling is the drastic variability in the dates used across studies to denote PDMP implementation. Commonly used databases for research information regarding PDMPs fail to distinguish between the date on which a state's PDMP was statutorily implemented and when its modern form was fully funded and operational. This discrepancy accounts for significant variation in the literature regarding the relationship between PDMPs and the effects of opioid prescribing (Horwitz et al., 2018). This thesis intends to correct for these discrepancies by focusing only on modern PDMPs when they were fully funded and operational, in an attempt to uniformly examine the consequences of PDMP implementation in each state. The use of these corrected dates makes this study a novel, and more precise, examination of PDMP implementation over this extended time series between 1999 and 2017.

IV. Data and Methodology

Empirical Strategy

This thesis will analyze the relationship between PDMPs and several different outcome variables, which can broadly be broken down into the categories of Prescribing, Deaths, and Crime. To model these various relationships, I estimate an ordinary least squares regression model for each outcome variable, using the following general equation:

$$Y_{1\ldots8_{st}} = \alpha_1 + \beta_2 NonMandatoryPDMP_{st} + \beta_3 MandatoryPDMP_{st} + \delta X_{st} + \gamma_t + \gamma_s + \gamma_s * t + e_{st}$$

Prior to transformations which will be described in detail below, the outcome variables for each model are:

Prescribing:	**Model 1:**	MMEs Per Capita
Deaths:	**Model 2:**	Total Opioid Death Rate
	Model 3:	Heroin Death Rate
	Model 4:	Synthetic Opioid Death Rate
	Model 5:	Other Opioid Death Rate
Crime:	**Model 6:**	Violent Crime Arrest Rate
	Model 7:	Property Crime Arrest Rate
	Model 8:	Drug Abuse Violations Arrest Rate

In each model, $\boldsymbol{\alpha}$ is a constant term and $\boldsymbol{X}$ is a matrix of control variables for naloxone access, pain management clinic ("pill mill") laws, Good Samaritan laws, Medicaid expansion, rates of uninsured, state GDP per capita, state unemployment rates, medical marijuana laws, and recreational marijuana laws.

In order to ensure robustness, these models control for state fixed effects (γ_s), year fixed effects (γ_t), and state trends ($\gamma_s * t$). I define state and year fixed effects as is done by Stock and Watson, that, "[f]ixed effects regression is a method of controlling for omitted variables in panel data when...some omitted variables are constant over time but vary across states...while others are constant across states but vary over time" (Stock and Watson, 2014). Because I control for these, I need not include a plethora of control variables, for much of the variation in the models are accounted for by the fixed effects.

I also control for trends in each state over time by creating 51 state dummy variables (one for each state and the District of Columbia). For each of these 51 variables, a value equal to each year is assigned for one given state (that for which the trend is accounting), and then a 0 is assigned for all years for all other states. This is to isolate the actual effect of each explanatory variable in light of ongoing trends within each state, in order to account "for systematic differential trends across implementation vs. non-implementation states prior to the policy" (Dave et al., 2018). For this model, the standard errors are clustered by the **State** variable in order to check for robustness. This is to account for the fact that, "unobserved components in outcomes for units within clusters are correlated" (Abadie et al., 2017).

These models employ the several standard assumptions of an ordinary least squares model. First, I assume validity of the model, or that, "the outcome measure should accurately reflect the phenomenon of interest... include all relevant predictors" and is generalizable (Gelman and Hill, 2007). In addition to including relevant economic and policy controls, the use of the fixed effects model also tries to control for omitted variables, enhancing validity. Linear models also assume additivity and linearity, or that the models' "deterministic component is a linear function of the of the separate predictors" (Gelman and Hill, 2007).

There are also three assumptions regarding the errors of the model. Linear models assume that errors are independent, of equal variance, and normally distributed (Gelman and Hill, 2007). Because errors are assumed to be independent, all explanatory variables in the model are therefore assumed to be exogenous, or "uncorrelated with the regression error term" (Stock and Watson, 2014). This is a critical assumption of these models—one made by all studies using linear regression to examine the relationship between PDMPs and these outcomes in the literature. This assumption is expressed mathematically in the following equation, with $\boldsymbol{X}$ representing all explanatory variables and $\boldsymbol{e_{st}}$ representing the error terms:

$$E(e_{st}|X) = 0$$

In contrast, the unequal variance of errors is a minor issue because it does not affect the form of predictor Xβ and the assumption that errors are normally distributed is of least importance because its does not interfere with the prediction of the regression (Gelman and Hill, 2007).

Description of Explanatory Variables

To capture the effectiveness of the varying degrees of mandatory status for the PDMP, I break the general PDMP into two separate explanatory variables: **Non-Mandatory PDMP** and **Mandatory PDMP**. I define Mandatory PDMPs as those which either require that physicians must be registered within the state's PDMP database in order to prescribe opioids

—a practice known as "mandatory registration"—or mandate that providers must check PDMPs before prescribing opioids to a patient—which is referred to as "mandatory access" (NAMSDL, 2015). The dates for mandatory enactment were gathered from the Prescription Drug Monitoring Program Training and Technical Assistance Center database (PDMP TTAC).

The data regarding the dates of operation for PDMPs were taken from a recent NBER working paper which documents inconsistencies in the relevant literature in identifying the dates that modern PDMPs went into effect (Horwitz et al., 2018). This paper clarifies that many sources fail to distinguish when PDMPs were nominally enacted, when they were funded, and when they were operational. These dates, which indicate when the state's modern PDMP system became fully funded and operational, are reproduced in **Table 1** below.

To code for PDMP implementation, I assign a 0 for all full years in which a PDMP of a given status was not operational, the fraction of the year in which the PDMP of a given mandatory status was operation in the enactment year (if enacted in January = 1.0, February = .9167, March = .8333...December = .0833), and a 1 for all following full years of operation in said mandatory status category. This calculation was necessary to be precise about the duration of PDMP operation in the year when it was first enacted or when its mandatory status changed.

Table 1

State	Date of Operational Modern PDMP
Alabama	April 2006
Alaska	January 2012
Arizona	December 2008
Arkansas	May 2013
California	September 2009
Colorado	February 2008
Connecticut	July 2008
Delaware	August 2012
Washington DC	October 2016
Florida	October 2011
Georgia	May 2013
Hawaii	February 2012
Idaho	April 2008
Illinois	December 2009
Indiana	July 2007
Iowa	March 2009
Kansas	April 2011
Kentucky	July 1999
Louisiana	January 2009
Maine	January 2005
Maryland	December 2013
Massachusetts	January 2011
Michigan	January 2003
Minnesota	April 2010
Mississippi	July 2008
Missouri	No PDMP
Montana	October 2012
Nebraska	January 2017
Nevada	February 2011
New Hampshire	October 2014
New Jersey	January 2012
New Mexico	August 2005
New York	June 2013
North Carolina	July 2007
North Dakota	October 2008
Ohio	October 2006
Oklahoma	July 2006
Oregon	September 2011
Pennsylvania	August 2016
Rhode Island	September 2012
South Carolina	February 2008
South Dakota	March 2012
Tennessee	January 2010
Texas	August 2012
Utah	January 2006
Vermont	January 2009
Virginia	June 2006
Washington	January 2012
West Virginia	May 2013
Wisconsin	June 2013
Wyoming	July 2013

Because data regarding PDMP dates of implementation are not uniformly reported throughout the literature or available databases, the dates of mandatory status enactment reported by the PDMP TTAC database came before the dates that PDMPs were fully operational, as reported in the Horowitz paper, for a few states.[1] This discrepancy is due to the fact that the PDMP TTAC database, from which mandatory status data was gathered, only accounts for the nominal, statutory date of enactment, and not the real date in which these policies took effect. To correct for this, I updated the dataset to report that mandatory provisions for these states took place at the same time as the operational enactment of the PDMP.

These models also control for economic climate and several indicators of a state's health and drug policy regime. As proxies for economic climate, I use both state unemployment and state GDP figures for the years 1999-2017. These data were taken from the Federal Reserve Economic Data database (FRED). It is necessary to control for economic climate in these models in order to account for the varying economic conditions across the states and how these may contribute to opioid use. Case and Deaton (2017) find that that declining economic conditions are associated with increases in drug use and fatalities. Thus, in measuring the

[1] These states/federal districts were Arizona, Deleware, District of Columbia, Nevada, New Hampshire, Pennsylvania, and West Virginia,

relationship of these economic measures with overdose deaths, I am able to further evaluate this "Deaths of Despair" hypothesis.

Similarly, by controlling for medical and recreational marijuana laws one can isolate the effect of PDMPs on prescribing, holding constant access to medicinal substitutions for opioids such as marijuana. The data on state marijuana laws were taken from a paper by McMichael et al. (2018), which finds that, "recreational and medical cannabis access laws reduce the number of morphine milligram equivalents prescribed each year by 6.9 and 6.1 percent, respectively." In including these controls in the model, this finding can be further examined.

The variable capturing **Naloxone Access** denotes whether a given state adopted laws to allow access to naloxone, an opioid-antagonist drug which can "reverse an opioid overdose and prevent…unintentional deaths" (PDAPS, 2017). Data on the enactment of naloxone access laws were compiled from the National Institute on Drug Abuse's Prescription Drug Abuse Policy System database, and indicate when the state first allowed legal access to naloxone. The models also control for **Percent Uninsured** and **Medicaid Expansion**, as proxies for the availability of health care access for citizens in each state. Data for the former was taken from the Census Bureau's American Community Survey (ACS, 2018) and data for the latter, which is coded as a binary variable for the year of adoption, was collected from the Kaiser Family Foundation (KFF, 2019). Lastly, the model controls for **Pill Mill Laws**, or state licensing regulations on pain management facilities, and **Good Samaritan Laws,** or laws which protect individuals who intervene to help those who have overdosed from legal liability. Data on these regulations were also collected from the Prescription Drug Abuse Policy System database (PDAPS, 2018b; PDAPS, 2018a).

Descriptive statistics for these variables, as well as the outcome variables which will be described in detail below, are reported in detail in **Appendix A**.

Outcome Variable and Data on Prescribing (Model 1)

First, I will analyze the relationship between PDMPs and opioid prescribing. To calculate opioid prescribing rates, I collected data from the Drug Enforcement Agency Automated Reports and Consolidated Ordering System on retail drug purchases (DEA ARCOS). These annual reports document the quantity of prescription opioids in grams that were sold in a given state in a given year, for years 2001-2017. Because PDMPs only monitor controlled substances dispensed by "non-hospital pharmacies and practitioners," I included only opioids dispensed by pharmacies, practitioners, and mid-level practitioners—those whose prescribing levels would be monitored by the PDMP (SAMHSA). The ARCOS reports provide consistent prescribing data over this time series for the following opioids: codeine, buprenorphine, dihydrocodeine, oxycodone, hydromorphone, hydrocodone, levorphanol, meperidine, methadone, morphine, opium powdered, opium tincture, oxymorphone, alfentanil, remifentanil, sufentanil base, tapentadol, noroxymorphone, and fentanyl base.

The quantities of these drugs were reported in grams. Since each opioid varies in its potency, I calculated the morphine equivalence, an "equivalency factor [used] to calculate a dose of morphine that is equivalent to the ordered opioid" for the amount of each drug prescribed (Wolters Kluwer, 2018). This calculation standardizes potency across all drugs. The conversion factors used to calculate morphine equivalence were taken from the CDC, Centers for Medicare and Medicaid Services, ClinCalc Database, and are reported in **Table 2** below . To find the rate of MMEs per capita, I simply multiplied the total morphine equivalence in grams for each state-year by 1000 and then divided that number by the relevant state-year population. Data for the populations were taken from the United States Census (US Census Bureau, 2018).

Table 2

Opioid	Conversion Factor
Codeine	.15
Buprenorphine	30
Oxycodone	1.5
Dihydrocodeine	.25
Hydromorphone	4
Hydrocodone	1
Levorphanol	11
Meperidine	.1
Methadone	3
Morphine	1
Opium Powdered	1
Oxymorphone	3
Alfentanil	30
Remifentanil	200
Sufentanil Base	500
Tapentadol	.4
Noroxymorphone	8
Opium Tincture	1
Fentanyl Base	100

As demonstrated in **Figure 4a**, the data for prescribing is positively skewed. To correct for this, I take the prescribing rates, M_{st}, measured in MMEs Per Capita, and employ a logarithmic transformation on the variable to derive the new variable, $Y_{1_{st}}$ using the following equation:

$$Y_{1_{st}} = ln(M_{st})$$

This transformation is especially useful, given that all of the outcomes for prescribing are positive (Gelman and Hill, 2007). The newly transformed data is reported in **Figure 4b.** Because of this logarithmic transformation, the outcome variable for this model will be reported as the percent increase or decrease in prescribing with which each explanatory variables is associated.

Figure 4a

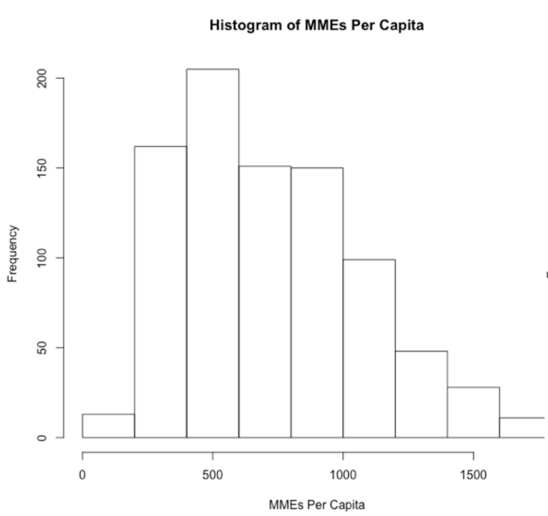
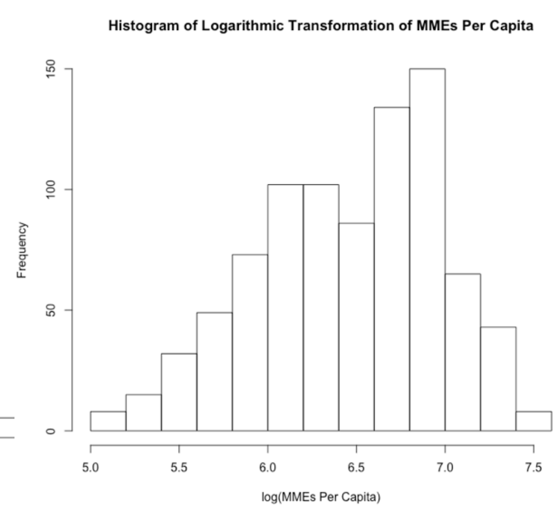


Figure 4b



Outcome Variables and Data on Overdose Deaths (Models 2-5)

I then turn to investigate the relationship between PDMPs and opioid overdose deaths. First, to calculate the **Total Death Rate** for a given state-year, I simply divided the quantity of total overdose deaths by the state's population in that year and multiplied by 100,000 in order to report the death rate per 100,000 residents. I repeated this process to find the **Heroin Death Rate**, **Synthetic Opioid Death Rate**, and **Other Opioid Death Rate**.

Consistent with much of the literature examining the effect of government policy on fatality rates, I also employ a logistic transformation on the outcome variables for the Total Opioid Death Rate, Synthetic Opioid Death Rate, Heroin Death Rate, and Other Opioid Death Rate (Dee, 1999; Miron and Tetelbaum, 1997; Berkson, 1953).

The methodology used in this literature holds that, "fatality rates are grouped data generated by a binary process," with that binary being whether or not a person dies from a drug overdose "in a given year" (Dee, 1999). Thus, I employ a logistic transformation which transforms the total death rate, T_{st}, "into the natural logarithm of the odds ratio," $Y_{2_{st}}$ (Dee, 1999). This equation is specified below:

$$Y_{2_{st}} = \frac{ln(T_{st})}{(1 - T_{st})}$$

I repeat this transformation for the Heroin Death Rate, H_{st}, which is transformed into the natural logarithm of the odds ratio, $Y_{3_{st}}$, the Synthetic Opioid Death Rate, S_{st}, which is transformed into the natural logarithm of the odds ratio, $Y_{4_{st}}$, and the Other Opioid Death Rate, O_{st}, which is transformed into the natural logarithm of the odds ratio, $Y_{5_{st}}$, using the following equations:

$$Y_{3_{st}} = \frac{ln(H_{st})}{(1 - H_{st})} \qquad Y_{4_{st}} = \frac{ln(S_{st})}{(1 - S_{st})} \qquad Y_{5_{st}} = \frac{ln(O_{st})}{(1 - O_{st})}$$

The data for opioid overdose deaths is taken directly from the CDC Wonder Database, which reports the causes of all recorded deaths from

1999-2017 in accordance with the International Classification of Diseases (ICD-10) mortality reporting codes (CDC Wonder, 2018).[2]

Outcome Variables and Data on Crime (Models 6-8)

Next, I will examine the effect of PDMP implementation on crime in the United States, specifically violent crime, property crime, and drug abuse violations. Similar to the overdose death rates, I again treat crime rates as "grouped data generated by a binary process" (Dee, 1999). In this instance, the binary describes whether or not someone was arrested for a crime in a given state-year. Therefore, I once again employ a logistic transformation on the variable for the Violent Crime Arrest Rate, V_{st}, to transform it into the natural logarithm of the odds ratio, $Y_{6_{st}}$, using the following equation:

$$Y_{6_{st}} = \frac{ln(V_{st})}{(1 - V_{st})}$$

[2] The codes that I used to identify total opioid deaths in a given year were Underlying Cause of Deaths Codes X40–X44, X60–X64, X85, and Y10–Y14 and 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 and unspecified narcotics). Similarly, for each of the specific drug death rates, I used the Underlying Cause of Deaths Codes X40–X44, X60–X64, X85, and Y10–Y14 and the relevant Multiple Cause of Death code (for example, T40.1 for isolated heroin deaths). This combination of codes is standard practice in the literature for determining opioid overdose death rates (See, for instance, Kennedy-Hendricks et al (2016))

I repeat this process for the Property Crime Arrest Rate, P_{st}, which is transformed into the natural logarithm of the odds ratio, $Y_{7_{st}}$, and for the Drug Abuse Violations Arrest Rate, D_{st}, which is transformed into the natural logarithm of the odds ratio, $Y_{8_{st}}$, using the equations:

$$Y_{7_{st}} = \frac{ln(P_{st})}{(1 - P_{st})} \qquad\qquad Y_{8_{st}} = \frac{ln(D_{st})}{(1 - D_{st})}$$

Crime statistics for each state and Washington, DC were taken from the FBI Uniform Crime Reporting Arrest database, a yearly report of crime statistics in the United States, for the years 1999-2017 (Bureau of Justice Statistics, 2018).

Violent crime is defined by the FBI as "offenses that involve force or threat of force," and is comprised of the offenses of murder and non-negligent manslaughter, rape, robbery, and aggravated assault. Property Crime is defined as "the taking of money or property, but [when] there is no force or threat of force against the victims," and is comprised of the offenses of burglary, larceny-theft, motor vehicle theft, and arson. Lastly, Drug Abuse Violations are defined as "state and/or local offenses relating to the unlawful possession, sale, use, growing, manufacturing, and making of narcotic drugs" (Bureau of Justice Statistics, 2019).

These statistics are presented in the Uniform Crime Reports as raw totals representing the total number of arrests in each category in a given state in a given year. Thus, to calculate the Violent Crime Arrest Rate for a given state-year, I divided the number of property crime arrests by the state's population in that year and multiplied by 100,000 to find the Violent Crime Arrest Rate per 100,000 residents. I repeated this process to find the Property Crime Arrest Rate and Drug Crime Arrest Rate.

Because the Uniform Crime Reports vary from year to year in the number of agencies reporting crime statistics in each state, I also include an interval explanatory variable for **Agencies Reporting** to control for this variation. Adding this variable allows one to isolate the effect of the PDMP on crime while accounting for the differences in the number of agencies reporting crimes in each state over time.

V. PDMPs and Opioid Prescribing

PDMPs are enacted by governments in an effort to reduce opioid prescribing (CDC, 2017). By creating a database that allows prescribers to view a patient's opioid history before writing prescriptions, this policy is designed to better inform practitioners about the opioid treatments that a patient has already received and to combat "doctor shopping," the practice of when a patient seeking opioids visits several providers in order to receive multiple prescriptions. Supporters of PDMPs argue that because prescribers are able to know the amount of opioids that a patient has already received, due to the availability of the PDMP database, they will be better informed about a patient's legitimate treatment needs and thus be less likely to prescribe to patients who already have a significant history of opioid consumption or who are seeking out opioids with an intent to use them for non-medical purposes.

I examine the relationship between PDMPs and opioid prescribing in **Model 1**, an ordinary least squares regression model. In this model, the outcome variable is the natural logarithm of MMEs Per Capita regressed on the aforementioned explanatory variables.[3] Because this model accounts for factors of state and year fixed effects, all coefficients are reported in relation to a baseline. In this model, the baseline state is Alabama and the baseline year is 2001. To check for robustness, this model clusters standard errors around the **State** variable.

Results

In **Model 1,** I find that Mandatory PDMPs are associated with a statistically significant reduction in opioid prescribing, as measured in ln(MMEs Per Capita). I also find evidence of a negative relationship between Non-Mandatory PDMPs and prescribing, though these findings are not significant at the .05 level. The results of this regression model are displayed below in **Table 3.** In addition to the magnitudes and standard errors for each variable, **Table 3** also reports statistical significance at the .1, .05, and .01 levels.

[3] These explanatory variables, once again, are Non-Mandatory PDMP, Mandatory PDMP, naloxone access, pain management clinic laws, Good Samaritan laws, Medicaid expansion, rate of uninsured, state GDP per capita, state unemployment rates, medical marijuana laws, and recreational marijuana laws. The model also controls for state fixed effects, year fixed effects, and state trends.

Table 3

	Dependent variable:
	ln(MMEs Per Capita)
Non-Mandatory PDMP	−0.039*
	(0.020)
Mandatory PDMP	−0.051**
	(0.025)
Good Samaritan Law	−0.037
	(0.028)
Pill Mill Law	0.0006
	(0.050)
PercentUninsured	0.001
	(0.005)
NaloxoneAccess	−0.014
	(0.022)
MML	0.037
	(0.022)
RML	0.054
	(0.044)
MedicaidExpansion	−0.032
	(0.035)
StateUnemployment	0.003
	(0.007)
StateGDPperCapita	−0.00001**
	(0.00000)
Constant	−12.004
	(9.23)
Observations	867
R^2	0.982
Adjusted R^2	0.979
Residual Std. Error	0.075 (df = 739)
F Statistic	322.2*** (df = 127; 739)
Note:	*p<0.1; **p<0.05; ***p<0.01

Regarding the PDMP variables, the coefficient for the Non-Mandatory PDMP variable is negative with a point estimate of -0.039. This suggests that, on average, the presence of an operational Non-Mandatory PDMP in a given state-year is associated with a reduction in MMEs Per Capita prescribed of 3.9%, in relation to the baseline. However, since this coefficient has a p-value of .058, one fails to reject the null hypothesis that there is no relationship between Non-Mandatory PDMPs and prescribing at the .05 level.

The coefficient for the variable representing PDMPs with mandatory requirements is also negative, with a point estimate of -.051. This coefficient is statistically significant at the .05 level and indicates that, on average, Mandatory PDMPs are associated with a 5.1% reduction in prescribing, relative to the baseline. Thus, one can reject the null hypothesis at the .05 level that there is no relationship between Mandatory PDMPs and prescribing.

The only other variable that has a coefficient which is statistically significant at the .05 level is that for State GDP per Capita. The coefficient for this variable is negative with a point estimate of .000001. This suggests that a $1 increase in state GDP per capita is associated with an average decrease in prescribing in that state-year of .0001% (or that every $100,000 increase is associated with a 1% decrease in prescribing), in relation to the baseline. Substantively, this provides evidence for the claim that there is a statistically significant, negative relationship between State GDP and opioid prescribing. None of the other variables is statistically significant at the .05 level.

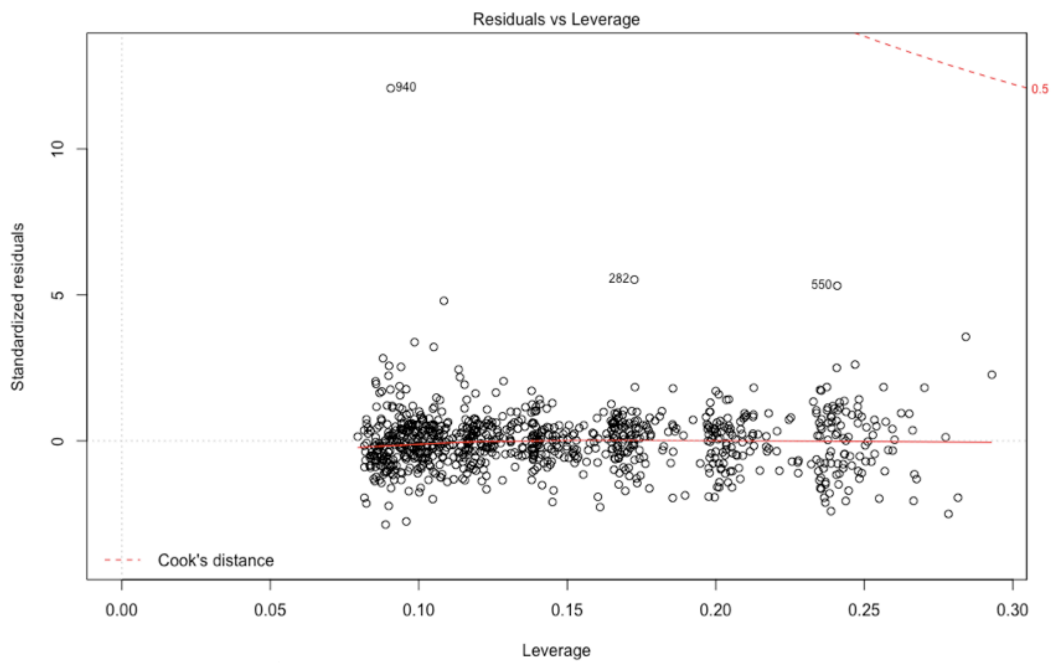
Model Fit and Outliers

Regarding the model fit, the Adjusted R^2 for **Model 1** is rather high, at .979. This indicates that a high level of variability of the outcome variable around its mean is explained by this model. Because this model controls for entity and time fixed effects, it is therefore able to mitigate many of the effects of an omitted variable bias, thus improving model fit.

There are three apparent outliers in this model, data points 940 (Wisconsin-2007), 282 (Indiana-2014), and 550 (Nevada-2016). The outlier of point 282 represents the year in Indiana in which prescribing peaked at 1576.61 MMEs per Capita. This peaking in prescribing occurs in the same year in which Indiana switched from having a Non-Mandatory PMDP to one with mandatory requirements. The outlier point 550 is likely caused by the fact that Nevada greatly increased prescribing of buprenorphine and methadone in 2016. These drugs make up a special class of opioids known as "Medically Assisted Treatments," or MATs. MATs are partial antagonist opioids which are often prescribed to treat those who are addicted to opioids because they are able to satisfy cravings without producing the same euphoric effect of other opioids (SAMHSA, 2015). Lastly, data point 940 seems to represent abnormal prescribing patterns for opium products in Wisconsin. The ARCOS report for 2007 shows that practitioners in Wisconsin ordered 5,237,333.33 grams of opium powdered, representing nearly all opium powdered ordered nationally that year. I chose to include these outliers in the model because they represent the data reported by the DEA in the ARCOS summaries.

As reported in **Figure 5,** the Cook's Distance, a measure of a given data point's influence on the overall regression model, of none of these outliers exceeds 0.5, indicating rather small influence. Thus, even if these figures are misrepresented in the government reports for those years, the influence of each outlier is rather inconsequential.

Figure 5



Discussion

Consistent with much of the relevant literature, **Model 1** provides evidence for the claim that at least some form of PDMPs is in fact associated with reductions in opioid prescribing. According to the model, PDMPs that have mandatory requirements are associated with a statistically significant decrease in prescribing.

Mandatory access provisions state that providers must consult the PDMP before prescribing opioids, allowing them to know a patient's opioid history. Absent PDMPs, providers must rely on a patient to be truthful about his or her prescribing history, facts that are not easily verifiable without these medical databases. According to one study surveying physicians in Wisconsin, "[t]he PDMP presented unexpected information about a patient's controlled substance prescription history or prescribers, and 34 percent of respondents indicated that the PDMP report confirmed that patients had prescription information that had not been disclosed" (Englebert, 2018). Therefore, by requiring a provider to check the PDMP before prescribing, Mandatory PDMPs work to decrease this gap in information between patients and providers and allow providers to make more informed decisions about a given patient's future opioid regimen.

Similarly, mandatory registration requirements work to strengthen the effectiveness of the PDMP at lowering prescribing as well. Prevalent in the literature surveying the relationship between prescribing and government regulations is the idea that heightened interventions and scrutiny of providers leads to a "chilling effect," or the "deterring [of] physicians from prescribing opioids to successfully treat a patient's pain...due to the potentially negative influence of drug enforcement agents monitoring their prescribing behaviors" (Reisman et al., 2009).

Mandatory registration laws require that all physicians must be enrolled in the state's PDMPs before being allowed to prescribe opioids. Thus, under these laws, all of a provider's prescribing activities are monitored and known to state law enforcement agents. Both state and federal law enforcement officials, such as the DEA, often consult PDMPs to determine irregularities in prescribing patterns or overprescribing from providers. For example, a recent raid on a pain management facility in Montgomery, AL on August 9, 2018, was catalyzed by "'extensive and alarming' prescribing habits" reported in the provider's Prescription Drug Monitoring Report (Hildreth and Henry, 2018).

Survey evidence suggests that some prescribers do in fact reduce prescribing and "underutilize controlled substances due to fear of legal repercussions" (Islam and McRae, 2014; Ross-Degnan et al, 2004; Turk et al, 1994). By mandating that a provider must be registered with the state's PMDP, this fear is likely heightened as the prescribing practices of all legally allowed prescriber are now directly monitored by the state. Thus, it is plausible that this "chilling effect" contributes to the decrease in prescribing associated with Mandatory PDMPs, indicated by this variable's negative point estimate in **Model 1**.

The results of **Model 1** also suggest that these mandates strengthen PDMPs in comparison to their non-mandatory form. The absolute value of the estimated magnitude of the coefficient for the Non-Mandatory PDMP, .039, is less than that for the Mandatory PDMP, which is .051, indicating that the mandatory provisions may lead to a stronger effect on reducing prescribing.

Without a mandate to access the PDMP before issuing an opioid prescription, it is up to the discretion of the physician to elect whether to consult the PDMP before prescribing. Because all providers legally need not access the PDMP, it is likely that under Non-Mandatory PDMP regimes, some providers may choose not to check the PMDP at all, lessening their impact and ability to inform providers about a patient's true opioid history. According to Chad Zadrazil of the National Alliance for Model State Drug Laws, "[u]ntil states began requiring physicians to use PDMPs, fewer than 35 percent of medical professionals used the tracking systems...in states that require doctors to consult PDMPs... physician usage rates exceed 90 percent" (Zadrazil, in Vestal, 2018). By mandating access to PDMPs, instead of relying on a provider's discretion, states can legally ensure that prescribers participate in these programs, further bridging the gap of information between prescribers and patients.

This finding that Mandatory PDMPs are associated with a statistically significant decrease in prescribing is supported by recent scholarship on the subject. In a recent study, Ayers and Jalal (2018) find that PDMPs reduce prescribing only "if they obligate doctors to check for patients' history prior to filling out a prescription...." In **Model 1**, the p-value for the Non-Mandatory PDMP is .058, providing some, but inconclusive, evidence that this type of PDMP may also be associated with a reduction in prescribing —potentially contrary to the findings of Ayers and Jalal. Still, this finding is technically not significant at the .05 level.

The timeliness of the Ayers and Jalal study gives it heightened importance in the literature. Much of the literature on the relationship between PDMPs and prescribing was conducted before the first Mandatory PDMP went into effect in Arizona in 2008 (See, for instance, Simeone and Holland, 2006). Thus, more recent studies such as this one provide a more comprehensive picture of the state of PDMPs in the United States because they distinguish between PDMPs which are voluntary and those which are mandatory. The findings of **Model 1**, as well as the Ayers and Jalal paper, suggest that this distinction is crucial in accurately evaluating the relationship between PDMPs and prescribing, given the differences in magnitudes and levels of significance among the coefficients for these respective variables.

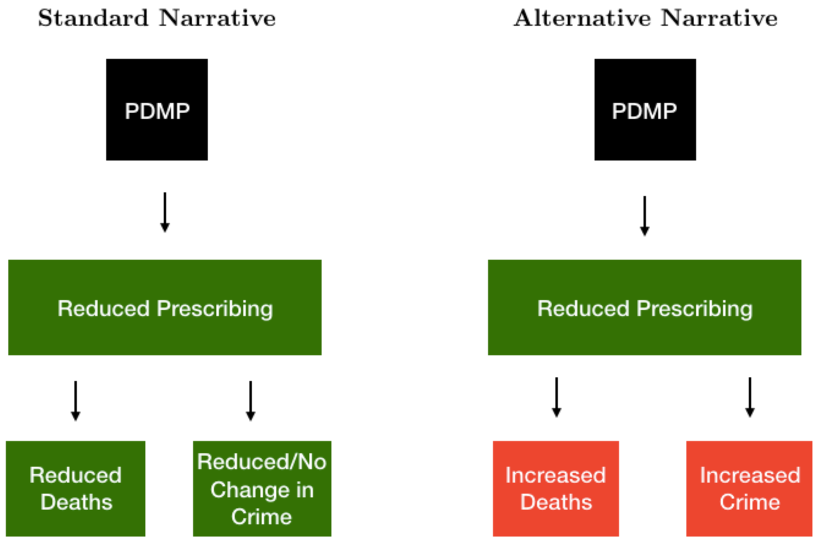
The statistically significant, negative relationship between State GDP per Capita and prescribing is also of interest. This finding is consistent with a recent report published by the United States Department of Health and Human Services, which claims that, "[p]overty, unemployment rates, and the employment-to-population ratio are highly correlated with the prevalence of prescription opioids...[o]n average, counties with worse economic prospects are more likely to have higher rates of opioid prescriptions" (Ghertner and Groves, 2018).

This increase in prescribing associated with falling GDP may be due to increased demand for opioids in times of economic hardship. Case and Deaton (2017) attempt to link economic downturn and increased opioid use, stating "increasing distress, and the failure of life...are consistent with people compensating through other risky behaviors such as abuse of alcohol and drug use...." Following this hypothesis, indicators of economic distress, like decreasing State GDP should be associated with increased prescribing, as it is in **Model 1.** However, I find no evidence of a statistically significant relationship between state unemployment—another proxy for economic climate—and prescribing, challenging this viewpoint.

Model 1 provides evidence for the claim that at least some form of the PDMP is associated with a statistically significant reduction in opioid prescribing, a claim that is promulgated by both proponents and critics of this policy. As explained in Chapter III and reproduced below in **Figure 3c**, the primary disagreement on the effectiveness of PDMPs between the two competing narratives is not over the program's relationship with prescribing, but how the negative relationship between prescribing and PDMPs affects the consequences of the decrease in prescribing—namely overdose deaths and crime. However, I chose to include this analysis of the relationship between PDMPs and prescribing to provide additional specific analysis on the relative effeteness of Mandatory PDMPs, which the literature lacks over this time series.

Figure 3c

Competing Narratives on the Effects of PDMPs



In this chapter, I find evidence that suggests that there is a statistically significant, negative relationship between Mandatory PDMPs and opioid prescribing. I also find weaker evidence for that there is a negative relationship between prescribing and Non-Mandatory PDMPs, but this relationship is not statistically significant at the .05 level. After analyzing that some form of the PDMP is associated with a statistically significant reduction in prescribing—a claim that is assumed by both the Standard Narrative and Alternative Narrative explaining the opioid crisis in the United States—I now turn to examine the relationship between PDMPs and overdose deaths.

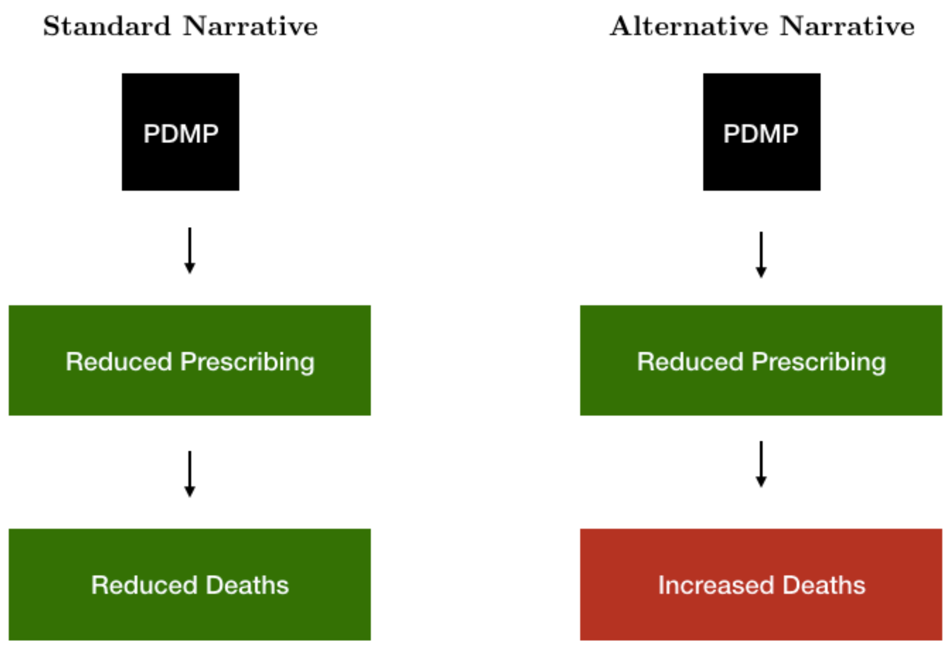
VI. PDMPs and Opioid Overdose Deaths

In the previous chapter, I find evidence that Mandatory PDMPs are associated with a statistically significant decrease in opioid prescribing. I also find weaker evidence of a negative relationship between prescribing and Non-Mandatory PDMPs (p-value = .058). Though these findings suggest the likelihood of a relationship between the PDMP types and decreased prescribing, this alone is insufficient evidence by which one can evaluate the effectiveness of the PDMPs—since the ultimate policy goal of PDMPs is not to reduce prescribing *per se*, but to reduce prescribing as a means for reducing opioid overdose deaths.

The Standard Narrative holds that since PDMPs work to reduce opioid prescribing, they also are effective in lowering overdose deaths because people will be prescribed fewer opioids, and thus, have less of a risk of becoming addicted and ultimately dying from drug abuse complications. The Alternative Narrative challenges this viewpoint, holding that the reduction in prescribing associated with PDMPs cuts people off from legal channels of access, thus creating a substitution to more dangerous illicit opioids, increasing the risk of overdose death. The respective conclusions of these narratives are again summarized below in **Figure 3d**.

Figure 3d

Competing Narratives on the Effects of PDMPs



In this chapter, I evaluate the validity of both of these claims by regressing the logistically transformed variables for **Total Opioid Overdose Deaths**, **Heroin Overdose Deaths**, **Synthetic Opioid Overdose Deaths**, and **Other Opioid Overdose Deaths** on the 2 PDMP categories, **Non-Mandatory PDMP** and **Mandatory PDMP**, as well as the aforementioned controls. By looking not only at the relationship between PDMPs and the Total Death Rate, but various subcategories for death rates, I am able to isolate the relative death rates for opioids most commonly acquired through legal channels—labeled as "other opioids"—from those most commonly acquired from the black market—heroin and synthetic opioids such as fentanyl. This allows me to analyze the hypotheses put forth by both the Standard Narrative and Alternative Narrative, for the latter specifies that illicit opioid overdose deaths will spike when legal channels of prescribing are limited (Miron et al., 2019).

Results on the PDMP Variables

The results for the least squares regression **Models 2**, **3**, **4**, and **5** are reported below in **Table 4**. Since these models control for State and Year fixed effects, the coefficients are reported in relation to a baseline. In all of these models, the baseline state is Alabama and the baseline year is 1999.

In **Model 2**, representing the relationship between PDMPs and the Total Opioid Death Rate, I find no evidence that either Non-Mandatory or Mandatory PDMPs are associated with a statistically significant reduction in total opioid deaths. To further investigate these relationships between PDMPs and deaths, I now turn to the results for the various subcategories.

Table 4

	Transformed dependent variable:			
	Total Rate	Heroin Rate	Synthetic Rate	Other Rate
	(2)	(3)	(4)	(5)
Non-Mandatory PDMP	−0.002	0.040	−0.002	−0.046*
	(0.016)	(0.059)	(0.062)	(0.026)
Mandatory PDMP	0.031	0.217**	0.019	−0.018
	(0.021)	(0.084)	(0.074)	(0.037)
Good Samaritan Law	0.064**	−0.076	0.101	0.090*
	(0.027)	(0.088)	(0.075)	(0.051)
Pill Mill Law	−0.062**	−0.169	0.013	−0.031
	(0.028)	(0.108)	(0.067)	(0.043)
Naloxone Access	−0.015	0.132**	0.011	0.004
	(0.021)	(0.062)	(0.088)	(0.057)
MML	0.046*	−0.113	0.071	−0.008
	(0.025)	(0.078)	(0.073)	(0.038)
RML	0.051*	−0.093	−0.013	0.081**
	(0.027)	(0.080)	(0.073)	(0.037)
Percent Uninsured	0.008*	−0.002	0.042***	0.011
	(0.004)	(0.015)	(0.013)	(0.009)
Medicaid Expansion	0.019	−0.321***	0.091	0.043
	(0.024)	(0.122)	(0.074)	(0.044)
State Unemployment	−0.005	−0.041	−0.044**	−0.001
	(0.005)	(0.028)	(0.019)	(0.010)
State GDP per Capita	−0.00000	−0.00001***	−0.00001	−0.00001**
	(0.00000)	(0.00001)	(0.00000)	(0.00000)
Constant	−0.675	−271.05***	−7.439	26.549***
	(7.940)	(18.680)	(13.865)	(9.031)
Observations	969	910	948	965
R^2	0.839	0.8799	0.8116	0.8414
Adjusted R^2	0.814	0.86	0.782	0.8169
Residual Std. Error	0.100 (df = 839)	0.3097 (df = 780)	0.2506 (df = 818)	0.1577 (df = 835)
F Statistic	33.86*** (df = 129; 839)	44.28*** (df = 129; 780)	27.32*** (df = 129; 818)	34.33*** (df = 129; 835)
Note:				*p<0.1; **p<0.05; ***p<0.01

The coefficient for Mandatory PDMPs is statistically significant in **Model 3**, which examines heroin deaths. The results of this model suggest that, on average, PDMPs with mandatory requirements are associated with an increase in the Heroin Death Rate of 21.7%, relative to the baseline. The coefficient for Non-Mandatory PDMPs in **Model 3** is not statistically significant at the .05 level.

In **Model 4**, which estimates the relationships between the PDMP categories and synthetic opioid overdose deaths, neither of the coefficients for the PDMP variables is statistically significant at the .05 level. Thus, I fail to reject the null hypothesis that there is no relationship between the Synthetic Opioid Death Rate and any type of PDMP.

Lastly, **Model 5** examines the relationship between the "Other" Opioid Death Rate—the death rate for natural and semi-synthetic opioids most commonly received through prescriptions—and the PDMP categories. Here, I find that Non-Mandatory PDMPs are associated with a reduction in the Other Opioid Death Rate of 4.6%, relative to the baseline. However, this coefficient is only significant at the .1 level, with a p-value of .08. Though this p-value is above the threshold required to reject the null hypothesis at the 0.05 level, this finding provides weak evidence of a negative relationship between Non-Mandatory PDMPs and the Other Opioid Death Rate. The coefficient for the Mandatory PDMP variable is not significant at any reasonably reliable level.

Discussion of PDMP Variables

Perhaps most strikingly, the results of **Model 2** find no evidence to suggest that PDMPs are effective in lowering the total rate of opioid overdose deaths as the Standard Narrative would suggest. In observing the total effect of PDMPs on overdose deaths, it appears that their implementation, in either their non-mandatory or stricter mandatory form, does little to contribute to mitigating the overall rate of opioid overdose deaths.

However, this is not to say that PDMPs have no effect on any type of opioid overdose death. The Alternative Narrative, promulgated by those who are skeptical of the effectiveness of PDMPs because of their potential unintended consequences, argues that an increase in illicit opioid deaths is likely to occur in the wake of PDMP implementation. This is due to the belief that when people cannot acquire their desired quantity of opioids from legal prescribing channels due by government regulations like the

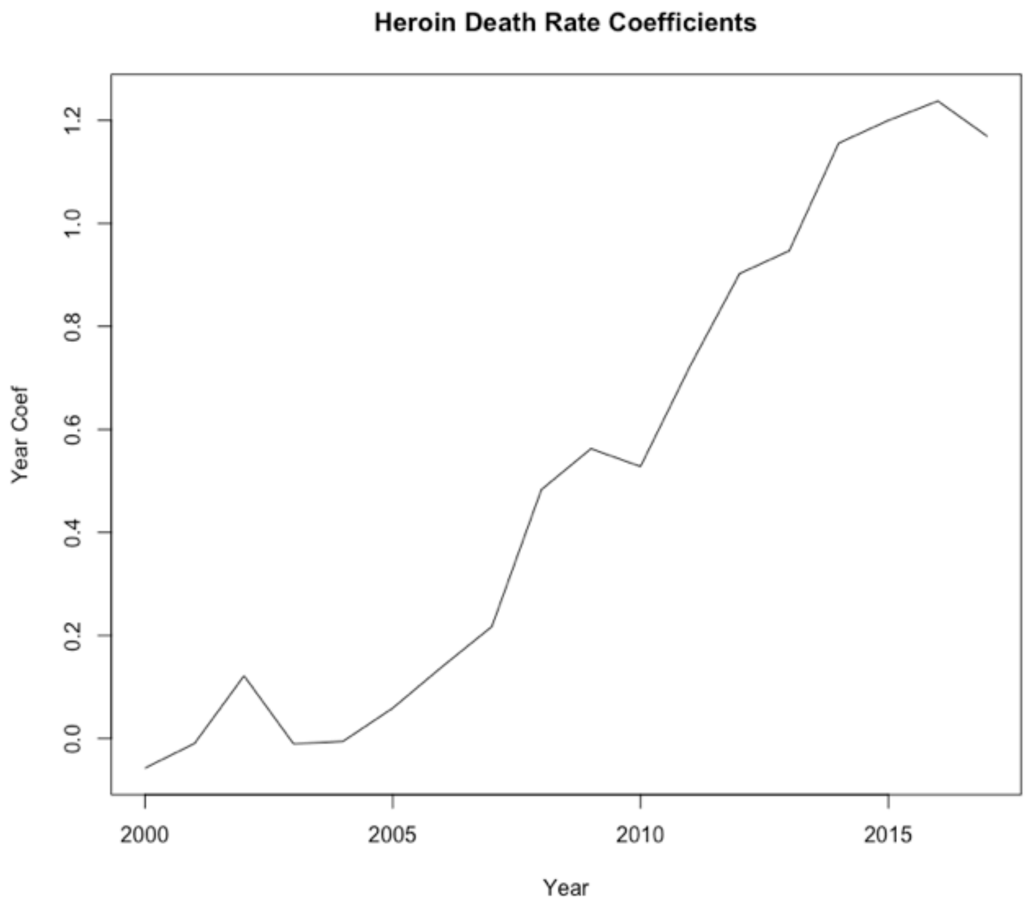
PDMP, they will turn to the black market to meet their demand for opioids (Miron et al., 2019). This hypothesis is supported by the findings of **Model 3**, which show that the implementation of a Mandatory PDMP is associated with a statistically significant average increase in the Heroin Death Rate of 21.7%. The relatively large magnitude of this coefficient suggests a rather striking association between the stricter PDMPs and heroin deaths. Thus, it appears that in the presence of these policies, opioid users substitute out the prescription opioids from which they are cut off for illicit opioids like heroin, contributing to an increase in the Heroin Death Rate.

This substitution to heroin compounds the risk associated with opioid use. In addition to heroin's heightened potency relative to that of most prescription opioids, "[d]rugs obtained in underground markets do not come with warning labels, and users cannot discuss safe use with their physicians, making them more likely to combine opioids with alcohol or other medications that suppress respiration" (Miron et al., 2019). Because heroin users lack this guidance from a physician or the ability to "easily assess the purity of the products they consume," they are at a higher risk of accidental overdose, and thus, overdose deaths (Miron et al., 2019). In moving opioid use away from legal channels towards the black market, restrictions on prescribing, such as PDMPs, seem to increase the dangers of opioid use by forcing users to substitute to more potent and lower quality drugs.

In addition to the PDMPs, other factors not explicitly addressed in **Model 3** may be contributing to this increase in heroin deaths. To investigate this, I plot the coefficients of the year fixed effects for this model, over the years 2000 to 2017, in **Figure 6** below. The year fixed effects represent factors that were uniform across states during this time series, but varied from year to year, such as changes in policy at the national level which influence the Heroin Death Rate.

The plot in **Figure 6** reports a defined spike in the value of the year coefficients in 2010. In 2010, Purdue Pharmaceuticals, the manufacturers of OxyContin, brought to market an "abuse deterrent" reformulation of the drug, that was more difficult to snort or inject due to its chemical composition (Zezima, 2011). While this decision was intended to reduce abuse of the drug, and subsequent overdose deaths, a recent study from the National Bureau of Economic Research finds that, "[t]he new abuse-deterrent formulation led many consumers to substitute to an inexpensive alternative, heroin," leading to a quadrupling in heroin deaths (Evans et al., 2018). Therefore, in addition to the stated effect of the PDMP, the reformulation of OxyContin may also be driving the increase in heroin deaths observed over this time series by diverting people towards the black market.

Figure 6

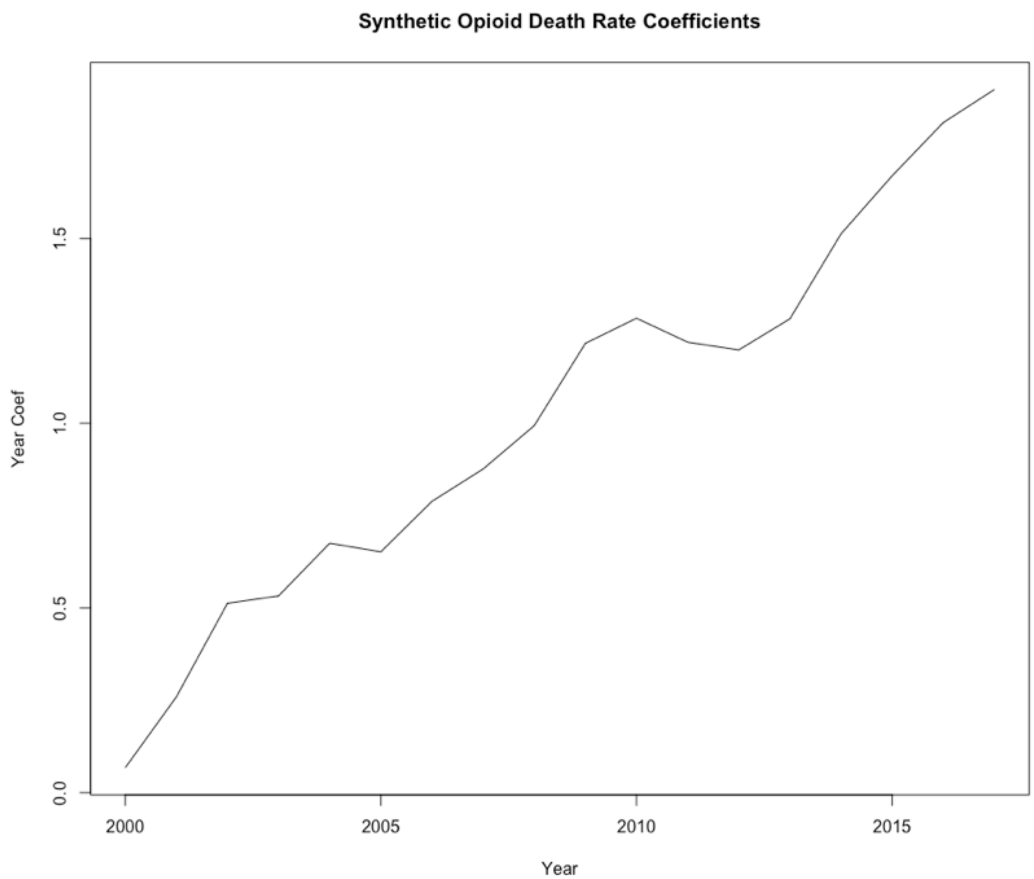


It is curious that I find no statistically significant relationship between any type of PDMP and the Synthetic Opioid Death Rate in **Model 4**. Much like heroin, synthetic opioids such as fentanyl are widely prevalent in illicit opioid markets, and thus are available substitutes for prescription opioids. According to the CDC, since 2013 deaths attributed to illicit synthetic opioids have been driving the opioid crisis in the United States. In fact, the rapid increase in fentanyl deaths, "[accounted] for nearly all the increase in drug overdose deaths from 2015 to 2016" (Dowell et al., 2017).

To further examine this relationship, I again plot the coefficients of the year fixed effects for **Model 4** below in **Figure 7** to identify factors that were not explicitly specified in the models that may influence the Synthetic Opioid Death Rate.

According to the plot of the fixed effects coefficients in **Figure 7**, the coefficients for the year dummies have been steadily rising over this time series of 2000-2017, with a pronounced spike around 2013. One factor independent of PDMP implementation that may help to explain the increase in synthetic opioid deaths at this time could be the rapid increase of illicit fentanyl distribution in the United States. According to one report, "[s]tarting in 2013, the production and distribution of [illicitly manufactured fentanyl] increased to unprecedented levels, fueled by increases in the global supply, processing, and distribution of fentanyl and fentanyl-precursor chemicals by criminal organizations" (Gladden et al., 2016).

Figure 7



With this increased prevalence of illicit fentanyl in the United States at this time, it is plausible that the rapid influx of synthetic opioids on the black market worked to contribute to the rise in the Synthetic Opioid Death Rate. Evidence suggests that the increase in fentanyl deaths at this time was driven by illicitly acquired fentanyl, rather than fentanyl acquired through legal prescribing channels (Gladden et al., 2016).

Fentanyl is also significantly cheaper to produce than other opioids. Because of fentanyl's relatively high potency, a dose of fentanyl of equivalent weight to that of heroin can be manufactured at "1/300 or 1/400 of the wholesale price of heroin" (Mars et al., 2018). The low production costs of fentanyl and the rapid increase of its supply on the US black market worked to drive the street price of fentanyl down and establish this drug as a cheap alternative to prescription opioids or heroin. This "supply shock" hypothesis represents an explanation for the increase in fentanyl deaths independent of restrictions on prescribing such as the PDMP. Because fentanyl could be easily acquired at a low price, opioid users chose to switch to fentanyl not necessarily because they were cut off from legal prescribing channels, but because fentanyl was the most cost-effective way to meet their demand for opioids.

The plot of the fixed effects in **Figure 7** demonstrates that circumstances uniform at the national level—independent of PDMP implementation—

had a notable, positive relationship with the increase in the Synthetic Opioid Death Rate over this time series. The defined spike in this graph after 2013 is likely explained by the rise of cheap fentanyl expanding the prevalence of synthetic opioid use and overdose deaths in the United States.

In **Model 5**, which analyzes the relationship between PDMPs and the Other Opioid Death Rate, the coefficient for Non-Mandatory PDMPs is associated with a 4.6% average reduction in opioid deaths. This opioid subcategory is made up of "natural and semi-synthetic" opioids, such as oxycodone and codeine—those that are most commonly prescribed by a physician through legal channels. In the previous chapter, I find weak evidence that Non-Mandatory PDMPs are associated with a decrease in the opioid prescribing rate (p-value = .058). In accordance with the Standard Narrative, this finding seems to support the claim that PDMPs, by reducing opioid prescribing, work to lower at least prescription opioid overdose deaths—those most directly impacted by limits on prescribing.

However, when analyzing the effectiveness of any public policy in meeting its desired goal, it is necessary to weigh the costs relative to the benefits. While it appears that when prescribing is decreased, the rate of prescription opioid deaths also decreases, this seems to have no relationship with the Total Opioid Overdose Rate. I also find evidence that the reduction in legal prescribing brought on by PDMPs is associated with an increase in heroin deaths, indicating that substitution from prescription to illicit opioids may have occurred in the wake of these restrictions. Therefore, it appears that the socially beneficial effect of reducing prescription opioid overdose deaths is greatly mitigated or eclipsed by the increase in deaths due to increased use of heroin acquired on the black market.

It is also important to take into account the fiscal costs of these programs. According to a 2009 study on the costs of PDMPs, the initial implementation of the PDMP can cost anywhere from $450,000 to $1,500,000. The report also notes that the "annual operating costs range from $125,000 to nearly [$1,000,000], with an average annual cost of about $500,000" (Maryland Advisory Council, 2009). While this sum of funding certainly does not make up a significant share of any state's annual budget, it seems counterproductive that a state would spend any revenue whatsoever on programs which evidence suggests may actually contribute to heightened rates of certain opioid overdoses without clear evidence of a net reduction in total opioid overdose deaths.

The findings of the PDMP coefficients in these models provide evidence against the widely held claim that PDMPs are an effective means of lowering the rate of total opioid deaths. Instead, I find that while PDMPs may be associated with a reduction in prescription opioid deaths, their enactment is also associated with a substitution to heroin, indicated by the rising heroin rate in the presence of the Mandatory PDMP, providing evidence for a substitution to heroin which greatly reduces any of the gains made by the reduction in prescription opioid deaths.

Results and Discussion of Control Variables

In addition to the PDMP variables, these models also include observations on several different control variables which may contribute to a state's opioid death rates. Notable is the relationship between overdose deaths and the proxies for economic conditions—**State GDP per Capita** and **State Unemployment**. **Model 3** indicates that an increase in State GDP per Capita of $100,000 is associated with an average decrease in heroin deaths of 1%. The coefficient for this variable is statistically significant at the .05 level. This finding indicates that there is a relationship between economic growth and decreased heroin deaths, an observation not easily explained by the logic of either the Standard or

Alternative Narratives—which mainly focus on the effect of prescribing restrictions.

An additional hypothesis might help explain this observation. In their paper, "Mortality and Morbidity in the 21st Century," Case and Deaton (2017) hold that, "increases in deaths of despair are accompanied by a measurable deterioration in economic and social wellbeing." According to this hypothesis, because of economic hardship, people turn to narcotics such as opioids as a means of escapism, increasing drug use, and thus, the risk overdose.

However, this hypothesis that declining economic conditions contribute to rising levels of opioid deaths is challenged by the findings of **Model 4**. Here, I find that a 1% increase in state unemployment is actually associated with a statistically significant 4.4% average decrease in synthetic opioid deaths, relative to the baseline. This appears to be at odds with the "Deaths of Despair" Hypothesis, which would predict that rising unemployment, a proxy for economic downturn, and deaths are positively related. Furthermore, I find no statistically significant effect of either state GDP per capita or state unemployment rates on the Total Opioid Death Rate.

The Case and Deaton paper focuses mainly on the morbidity rates of non-Hispanic whites aged 45-54, while this study models the effect of these variables on the general population. Thus, the theory that varying economic conditions are associated with increased opioid deaths may only apply to this specific demographic group, and not on the population as a whole. Given the contrasting findings of **Models 3** and **4**, which both examine the relationship between these economic proxies and common illicitly acquired opioids, this question is left unresolved and should merit future research on the relationships between economic conditions, demographic groups, and overdose deaths, which is beyond the scope of this thesis.

The coefficients on the proxy controls for the availability of healthcare in a state—**Medicaid Expansion** and **Percent Uninsured** are also notable. **Model 3** suggests that, on average, states which expand Medicaid experience a statistically significant decrease in the Heroin Death Rate of 32.1%, relative to the baseline. One hypothesis explaining this fairly dramatic decrease in heroin deaths is the fact that when states expand access to healthcare through Medicaid, access to Medically Assisted Treatments (MATs), or drugs used to treat opioid addiction, increases. According to a 2019 study on the effect of Medicaid expansion on opioid treatments, "[g]rowth in prescriptions used to treat opioid use disorder greatly outpaced other drugs, suggesting important gains in access to addiction treatments" (Cher et al., 2019). By providing greater access to legal MATs, such as buprenorphine and methadone, Medicaid expansion allows users to better treat their drug addictions, likely working towards creating this decrease in heroin deaths.

Additionally, Medicaid expansion appears to expand access to legal channels of opioid prescribing, as "overall prescription use per enrollee was higher after 2014," the year in which the Affordable Care Act first "prompted some states to expand Medicaid programs, providing low-cost prescription access to millions of Americans" (Cher et al., 2019). Because users of opioids were able to better access opioids through legal channels under Medicaid expansion, they did not need to resort to the black market to meet this demand through illicit drugs. Thus, by increasing access to both MATs and legal channels of prescribing, the substitution effect to the black market which occurs in the wake of prescribing seems to have been mitigated.

The Standard Narrative would predict that this increase in prescribing due to Medicaid expansion would be associated with an increase in prescription opioid overdose deaths, as more people are able to gain access to opioids. However, in **Model 5**, I find no evidence of a statistically significant relationship between Medicaid expansion and the death rate for those opioids most commonly received from a prescription. Therefore, it appears that in increasing access to legally prescribed opioids, Medicaid expansion worked to lower overdose deaths by decreasing the substitution to the black market.

There also is a statistically significant, positive relationship between the percent of people who are uninsured in a state and the Synthetic Opioid Death Rate. According to **Model 4**, a 1% increase in the uninsured rate is associated with a 4.2% average increase in the Synthetic Opioid Death Rate, relative to the baseline.

This increase is likely occurring for two principal reasons. First, in accordance with findings of Cher et al., increased access to healthcare through insurance provides individuals with greater access to legal prescription opioids. Thus, when fewer people are insured, fewer people are able to acquire low cost prescription drugs through legal channels, making this substitution to illicit fentanyl, and ultimately fentanyl overdose deaths, more likely. Second, access to MATs is far more prevalent for those who are insured, as "[m]ost commercial insurance plans...cover some opioid-addiction medications—most commonly buprenorphine" (Volkow et al., 2014). As rates of the uninsured increase, fewer people can access these drugs and adequately treat their addiction with them. The results on both the variables for Medicaid expansion and the rate of the uninsured suggest that expanded access to healthcare helps to reduce illicit opioid overdose death by providing access to legally prescribed opioids and expanding the prevalence of addiction treatment drugs.

The variable representing the expansion of **Recreational Marijuana Laws** (RML) also provide interesting insights into the relationship between expanded access to legal drugs and opioid overdose deaths. In **Model 5**, I find that the enactment of an RML is associated with an average increase in the Other Opioid Death Rate of 8.1%, relative to the baseline state-year pair. This finding is significant at the .05 level.

This result is at odds with much of the relevant literature examining the relationship between marijuana legalization and opioid use. According to one study surveying the effect of recreational marijuana legalization in Colorado, "Colorado's legalization of recreational cannabis sales and use resulted in a 0.7 deaths per month...reduction in opioid-related deaths" (Livingston et al., 2017). This study argues that because legal marijuana is available as a substitute for opioids in treating chronic pain, fewer people would need to be prescribed opioids, thus lowering the potential risk of overdose.

Still, in **Model 1** in the previous chapter, I find no statistically significant relationship between RML and prescribing. Therefore, I find no evidence that legalization of marijuana reduces the amount of opioids prescribed by physicians, potentially challenging this hypothesis once other policies are controlled for.

Curiously, I find a statistically significant, negative relationship between **Pill Mill Laws** and the Total Opioid Death Rate. **Model 2** suggests that the enactment of Pill Mill Law is associated with an average decrease in the Total Opioid Death Rate of 6.2%, relative to the baseline. Specifically, these laws are regulations on pain management clinics which mandate that practitioners must receive state certification and comply with staffing regulations (PDAPS, 2018b). Much like the PDMP, the goal of these policies is to curb opioid prescribing by monitoring the activities of these facilities.

However, I find no evidence to suggest that Pill Mill Laws have any relationship with prescribing. In **Model 1** in the previous chapter, which measures among other things the relationship between Pill Mill Laws and prescribing, the magnitude of the coefficient for this variable is nearly 0, with a p-value of .99—indicating that there is no evidence of a statistically significant relationship between these variables. Other studies have found that the enactment of these laws has had only "modest effects" on prescribing (Rutkow et al., 2015).

According to Dr. Darius Rastegar of Johns Hopkins School of Medicine, these regulations are "only modestly effective [at reducing prescribing]... because they only affect the outliers. Most of the prescription opioids that are fueling the current epidemic are not coming from 'pill mills'" (Rastegar, 2015). Therefore, the reduction in deaths associated with these regulations may likely be due to a factor independent of the relationship between prescribing and deaths that the Standard Narrative would suggest.

Following Rastegar's analysis, increasing oversight of pain management clinics may indeed root out the most egregious practices of overprescribing. Still, in **Model 5**, I find no evidence that these policies are associated with a decrease in the specified Other Opioid Death Rate, consisting of opioid deaths caused by prescription drugs—those that would be acquired from a pain management clinic. Furthermore, these regulations appear to be rather non-invasive into the practices of pain management clinicians. For example, in only 1 of the 12 states which have passed Pill Mill Laws—West Virginia—do these laws specify defined prescription limitations on the duration of an opioid treatment regimen (PDAPS, 2018b). Instead, these laws mainly focus on continued licensing and certification requirements, rather than specifically addressing prescribing practices.

Given the relatively recent advent of Pill Mill Laws and the fact that only 12 states to date have adopted any form of them, this question of the causes behind the relationship between Pill Mill Laws and opioid overdose deaths is left unresolved by the findings of this study alone and should merit future exploration on the subject as more states adopt this policy.

Lastly, I find evidence of both a statistically significant, positive relationship between **Naloxone Access** and the Heroin Death Rate, and **Good Samaritan Laws** and the Total Opioid Death Rate. **Model 3** suggests that the expansion of naloxone access is associated with a 13.2% increase in the Heroin Death Rate, while **Model 2**, suggests that the enactment of a Good Samaritan law is associated with a 6.2% increase in the Total Opioid Death Rate, both in relation to the baseline state-year of Alabama in 1999.

These results are certainly at odds with the literature advocating for the expansion of immunity laws as a means to reduce the risk surrounding opioid use. Naloxone is an "opioid antagonist that is used to temporarily reverse the effects of an opioid overdose, namely slowed or stopped breathing." According to the US Surgeon General Jerome Adams, "[e]xpanding the awareness and availability of this medication is a key part of the public health response to the opioid epidemic" (Adams, 2019). In conjunction with expanded legal availability of naloxone, Good Samaritan laws protect individuals who help assist people experiencing overdoses—such as by administering naloxone—by protecting them from legal prosecution in the case of error in administering care or eventual overdose death.

Proponents of these laws argue that by increasing access to the overdose antidote naloxone, while also protecting those who administer it from legal liability, opioid deaths should decrease as the risks of opioid use are reduced by the availability of this overdose-reversing drug. In support of this claim, McClellan et al. (2018) find that, "[n]aloxone access and Good Samaritan Laws are associated with 14% and 15% reductions, respectively, in opioid overdose deaths." However, McClellan explicitly does not control for PDMP implementation, differentiating its methodology from the empirical strategy of this thesis. Therefore, given these vastly differing results, the addition of the PDMP variables in this thesis may provide a new perspective on the efficacy of naloxone access and Good Samaritan laws, when controlling for other policy factors which may affect overdose deaths.

Even in spite of this debate in the literature, the results of these models suggest a statistically significant, positive relationship between the risk-reduction laws and overdose deaths. One hypothesis which may better explain these apparently surprising findings is that a moral hazard emerges with the implementation of these laws. In short, a "moral hazard" describes a situation in which "one party gets involved in a risky event knowing that it is protected against the risk" (Economic Times, 2019). In the context of drug use, this would mean that people would feel more inclined to use opioids under regimes which allow access to naloxone or have Good Samaritan laws because they *believe* that the risk of overdose is greatly mitigated.

In a recent study entitled "The Moral Hazard of Lifesaving Innovations: Naloxone Access, Opioid Abuse, and Crime," Doleac and Mukherjee (2018) examine this hypothesis, finding that, "[w]hile naloxone has great potential as a harm-reduction strategy, [their] analysis is consistent with the hypothesis that broadening access to naloxone encourages riskier behaviors with respect to opioid abuse." In addition, this study finds that naloxone access expansion is associated with increased use of fentanyl and increased opioid mortality. As such, some evidence in the literature does suggest the possibility of the advent of a moral hazard as an effect of these laws, supporting the findings of these models.

Summary of Results

In this chapter, I show that Mandatory PDMPs are indeed associated with an increase in heroin deaths, indicating a striking substitution to illicit opioids as a response to these prescribing restrictions. While I do find some evidence demonstrating that Non-Mandatory PDMPs are associated with a decrease in deaths caused by the type of opioids most commonly acquired through legal prescriptions, these decreases are likely offset by an unintended substitution to heroin in the wake of PDMP restrictions, demonstrated by the ambiguous effect of either PDMP specification on the Total Opioid Death Rate.

In analyzing the various controls in these models, I find rather inconclusive results on the respective relationships between marijuana legalization, state economic climate, and Pill Mill Laws, and opioid overdose deaths—as my findings differ from leading theories presented in the literature. In addition, my analysis of risk-reduction laws such as naloxone access laws and Good Samaritan laws challenges the mainstream belief of these laws' effectiveness in reducing overdose deaths and presents some evidence of an unintended moral hazard which encourages drug use in states that have enacted these laws. Lastly, I also observe strong evidence that the expansion of access to healthcare in the United State—proxied by Medicaid expansion and the rate of the uninsured—can work to reduce opioid overdose deaths by increasing access to safer, legal channels of prescribing and opioid therapy treatments used to combat addiction.

VII. PDMPs and Crime

I now turn to examine whether the decrease in prescribing associated with PDMPs has any bearing on potential unintended spillovers into crime rates. While the PDMP is a policy instrument aimed at lowering opioid overdose deaths, its negative relationship with prescribing may also impact these other variables, even if they are not the intended focus of the policy. The Alternative Narrative holds that with policy intervention often comes unintended effects on outcomes related to, but not directly targeted by, said policy. Applied to crime in the wake of drug restrictions, this narrative predicts that increased regulations on prescribing should affect crime in three ways.

First, "[i]f crimes are committed to finance drug consumption, prohibition should increase crime by raising prices" (Miron and Zwiebel, 1995). By restricting access to opioids, and thus increasing their scarcity, the cost of drugs on the black market should increase, leading some people to commit property crime in higher rates in order to finance their, now more expensive, purchases. This hypothesis is supported by several quantitative studies which find that restrictions not only increase the black market prices of illicit drugs, but also the rate of income-generating property crime (Benson and Rasmussen, 1991; Benson et al., 1992; Silverman and Spruill, 1977).

Second, the Alternative Narrative predicts that restrictions such as PDMP should be associated with increases in violent crime as well. As highlighted in the previous chapter, the substitution to illicit opioids under restrictive drug regimes seems to lead people away from legal channels of purchase and toward the black market. Concurrently, since "participants in the illegal drug trade cannot use the legal and judicial system [to enforce transactions], the...benefits to using violence to resolve disputes increases" (Miron and Zwiebel, 1995). In the wake of prescribing restrictions pushing more people to the unregulated black market, violent crime should increase as a means to enforce disputes in the absence of legal mechanisms of enforcement.

Lastly, the Alternative Narrative holds that drug abuse violations should increase as a response to heightened restrictions. The FBI's definition of "drug abuse violations" is rather expansive, covering all offenses "relating to the unlawful possession, sale, use, growing, manufacturing, and making of narcotic drugs" (Bureau of Justice Statistics, 2019). As more people turn to the illicit market for drugs, the rate of people being arrested for the purchase or sale of these drugs should increase if enforcement of existing laws remains constant.

In order to test these hypothesized relationships, I regress the transformed outcome variables for the **Property Crime Arrest Rate**, **Violent Crime Arrest Rate**, and **Drug Abuse Violation Arrest Rate** on the 2 PDMP variables, **Non-Mandatory PDMPs** and **Mandatory PDMPs**, the matrix of controls, the year and state fixed effects, and state trends. In addition to the aforementioned controls, for the three models examining crime rates, I add an additional variable—**Agencies Reporting**—to control for variations in the number of agencies reporting in each state over the time series of 1999-2017.

Results and Discussion

The results of **Models 6**, **7**, and **8** are reported below in **Table 5**. In all of these models, the baseline state-year pair is Alabama in 1999. Neither the coefficient for Non-Mandatory PDMPs nor that for Mandatory PDMPs is statistically significant at any reliable level in any of the crime models. Furthermore, the point estimates for these coefficients is less than .01 in each model, indicating that these models find no evidence of an

Table 5

	Transformed dependent variable:		
	Violent Crime Arrest Rate	Property Crime Arrest Rate	Drug Crime Arrest Rate
	(6)	(7)	(8)
Non-Mandatory PDMP	0.001	−0.0002	−0.0003
	(0.001)	(0.0002)	(0.0004)
Mandatory PDMP	0.001	−0.0002	−0.001
	(0.001)	(0.0003)	(0.0007)
Good Samaritan Law	0.003	0.00001	0.001
	(0.004)	(0.0005)	(0.0007)
Agencies Reporting	0.0001	0.00001	0.0001
	(0.00001)	(0.00000)	(0.00000)
Pill Mill Law	0.007	0.0003	0.0002
	(0.007)	(0.0005)	(0.004)
Naloxone Access	−0.0005	−0.0002	0.0004
	(0.001)	(0.0002)	(0.0004)
MML	−0.0001	0.0003	0.001*
	(0.001)	(0.0002)	(0.0006)
RML	−0.001	−0.001	−0.001
	(0.001)	(0.0009)	(0.001)
Percent Uninsured	0.0001	−0.00005	0.00004
	(0.0002)	(0.00008)	(0.0003)
Medicaid Expansion	−0.006	−0.0005	−0.001
	(0.005)	(0.0004)	(0.0006)
State Unemployment	−0.0003	−0.00001	−0.0003*
	(0.0003)	(0.0001)	(0.0002)
State GDP per Capita	0.00000	0.00000	−0.00000
	(0.00000)	(0.00000)	(0.00000)
Constant	7.785***	0.358**	1.451***
	(.480)	(0.174)	(0.276)
Observations	948	951	951
R^2	0.6149	0.9576	0.922
Adjusted R^2	0.554	0.9509	0.9098
Residual Std. Error	0.008 (df = 817)	0.001 (df = 820)	0.0016 (df = 820)
F Statistic	10.03*** (df = 130; 817)	142.5*** (df = 130; 820)	74.75*** (df = 130; 820)

Note:
*p<0.1; **p<0.05; ***p<0.01

association between PDMP implementation and violent crime, property crime, or drug crime arrest rates. I also find no statistically significant relationships between any of the control variables and crime rates.

These findings certainly challenge the "unintended spillover" hypothesis promulgated by the Alternative Narrative. One factor explaining the negligible change in the property crime rate could be the relatively cheap price of illicit opioids. Recall that the mechanism by which the Alternative Narrative posits that the property crime will increase is that as opioid access becomes more restricted, drug prices will rise, leading people to commit more income-generating crime to fund consumption. However, the price of opioids on the black market has actually decreased in the United States since the 1990s, likely due to an increase in the supply of Colombian-sourced drugs (Rosenblum et al., 2014). It seems that the increase in the supply of illicit opioids has contributed greatly to offsetting price rises that may have arisen due to restrictions, thus mitigating the need for more income-generating property crimes.

In addition, recent scholarship on the relationship between PDMPs and property crime have found no statistically significant relationship between these variables. For example, Dave et al. (2018) find that neither Non-

Mandatory nor Mandatory PDMPs are associated with any change in property crime, supporting the findings of **Model 7**.

It is also curious that I find the drug abuse violations and violent crime rates to have no association with PDMP implementation. While the Dave et al. study—one of the first to comprehensively analyze the effect of Mandatory PDMPs on crime—does not find any relationship between either PDMP type and drug crimes, it does find a statistically significant, negative relationship between Mandatory PDMPs and violent crime. In fact, the authors note that the negative association they observe between the implementation of Mandatory PDMPs and the overall crime rate is "mainly driven by [the reduction in] violent crimes" (Dave et al., 2018).

However, this thesis is differentiated from the Dave et al. study in several important methodological ways. First, Dave and his colleagues do not control for the number of agencies reporting in each state-year. This choice of omission could be especially problematic, given the wide variety of agencies reporting in each state over the time series. In fact, the FBI cautions in its Unified Crime Reports that, "[b]ecause the number of agencies submitting arrest data varies from year to year, users are cautioned about making direct comparisons between [current year] arrest totals and those published in previous years' editions" (Bureau of Justice Statistics, 2018). Therefore, without these controls, the validity of Dave's study should be called into question, as many states greatly vary in the number of agencies reporting crime statistics over each year.

Second, Dave et al. interpret Mandatory PDMPs in a stricter sense, defining a state's PDMP as "mandatory" only when "states...require both physicians and pharmacists to register on and query the PDMP prior to prescribing and/or dispensing any controlled drug" (Dave et al., 2018). However, this strongest form of PDMP is a relatively new policy which states have adopted. The first Mandatory Access and Registration PDMP became operational in Arizona in 2011. Since then, states began to slowly adopt these provisions, with a plurality of adopting states doing so in 2016. By 2017, only 22 of the 50 states and the District of Columbia mandated both registration and access. Thus, Dave's specifications may not be able to fully analyze the effect of Mandatory Access and Registration PDMPs because of the relatively few years and states in which these PDMPs were operational. As states continue to adopt Mandatory Access and Registration PDMPs over time, this policy's relationship with prescribing can likely be more accurately studied as the sample size of years in which this policy exists increases.

Third, in their regression equation, Dave et al. include an interaction effect between the PDMP and the mandatory status to account for PDMPs which are mandatory. This choice to include an interaction is not methodologically appropriate, because in no instance would there be a coded 0 for PDMP implementation and a coded 1 for mandatory status, indicating that the mandatory variable is reliant on there first being a PDMP. Therefore, this relationship is not suitable to be represented as an interaction effect.

Next, unlike this study, Dave et al. do not perform a logistic transform on their outcome crime variables. In this thesis, I chose to transform the various crime rates into the natural logarithm of the odds ratio, consistent with much of the literature surveying binary outcomes such as whether or not one is arrested for a crime (See, for instance, Dee, 1999; Miron and Tetelbaum, 1997; Berkson, 1953). While the choice not to do so is not necessarily a fault of Dave's methodology, it does help to explain why the discrepancies between these two studies exist.

Lastly, and perhaps most powerfully, the dates used by Dave et al. to code for PDMP implementation do not account for when the PDMPs were fully funded and operational, as expressed by Horowitz et al. (2018). Thus, the difference in findings could also be attributed to the incorrect choice of dates which they used. These aforementioned differences in methodologies likely account for the diverging outcomes between my study and that of Dave et al. While Dave's study is one of the first to examine the effect of Mandatory PDMPs on crime, and should be recognized as a thought-provoking addition to a budding literature, its choices to include an inappropriate interaction effect and use of imprecise dates most notably undermine the validity of its findings, and should call into question its results.

In this chapter, I do not find sufficient evidence to support the Alternative Narrative's claim that PDMP implementation is associated with an unintended increase in crime rates as a response to decreased prescribing. Regarding the Standard Narrative, while these findings do not suggest a negative relationship on crime, by showing that there is no evidence of an unintended spillover effect I do in part buttress the Standard Narrative in demonstrating that the unforeseen costs of implementation hypothesized by the Alternative Narrative are not supported in the data. The policy goal of the PDMP is to lower opioid overdose deaths, and not necessarily to decrease crime. Thus, finding no evidence of spillovers at least does not weaken the Standard Narrative, for the PDMP does not appear to negatively impact these other outcomes.

VIII. Conclusion

In this thesis, I do not find evidence to suggest that either Non-Mandatory or Mandatory PDMPs are associated with any reduction in the Total Opioid Death Rate, challenging the legitimacy of the PDMP as an effective means of lowering overall overdose deaths. While in Chapter V I do find evidence that Mandatory PDMPs are indeed associated with a statistically significant average reduction in prescribing of 5.1%, as well as weaker evidence that Non-Mandatory PDMPs are associated with a 3.9% average reduction in prescribing, these negative relationships with prescribing alone are not sufficient in determining the ultimate effectiveness of the PDMP because the goal of this policy is to reduce prescribing *as a means of* reducing overdose deaths.

To explain the ambiguous relationship between PDMPs and total overdose deaths, I hypothesize that the decrease in prescribing creates a substitution to heroin, as some users are cut off from legal channels of prescribing due to heightened restrictions. This theory is supported by my findings in Chapter VI, which demonstrates that Mandatory PDMP implementation is associated with an average increase in the Heroin Death Rate of 21.7%. Given that I find no statistically significant relationship between PDMPs and the Total Opioid Death Rate, this increase in heroin deaths likely offsets any reductions in prescription opioid deaths that may be associated with PDMP implementation.

Regarding the two prevailing narratives in the literature used to explain America's opioid crisis, the findings of this thesis do not support the Standard Narrative's claim that the PDMP works to lower total opioid overdose deaths. Though the Standard Narrative is correct in predicting that PDMPs are successful in reducing the amount of MMEs per capita prescribed, I find no evidence that these restrictions in turn contribute to a decrease in the Total Opioid Death Rate.

I do, however, find weak evidence that Non-Mandatory PDMPs are associated with an average decrease in the Other Opioid Death Rate of 4.6%. This observation superficially validates the Standard Narrative's argument that by reducing prescribing, PDMPs can work to lower at least prescription opioid deaths. Nevertheless, analyzing the relationship between PDMPs and this subcategory of overdose deaths alone provides an incomplete picture of this policy's role in the opioid crisis. As the Alternative Narrative suggests, the simultaneous substitution to illicit heroin which arises in the wake of PDMP implementation serves as an unintended consequence of intervention, one which greatly mitigates any productive reduction in overall deaths.

In showing that PDMPs are in fact associated with a dramatic rise in heroin deaths, the findings of this thesis support the Alternative Narrative's criticism that PDMPs will not reduce the opioid deaths because of substitution to the black market. However, I do not find evidence that PDMP implementation is associated with an increase in income-generating or drug-related crime, indicating that unintended spillovers due to PDMP implementation predicted by the Alternative Narrative may be overstated.

Still, given that PDMPs do not reduce the Total Opioid Death Rate, and may contribute to an increase in heroin deaths, it seems that PDMPs are hardly an effective policy measure for reducing the overall count of opioid deaths in the United States.

The outcomes of this thesis challenge the widespread belief in the public discourse regarding the usefulness of PDMPs and seriously call into question the fervor among the policymaking community surrounding their implementation. Despite evidence suggesting its ineffectiveness in reducing total deaths and apparent contribution to increasing heroin deaths, the PDMP remains a popular policy tool that lawmakers at the state and federal level have championed as what they believe to be an effective measure for combatting the opioid crisis that is ravaging the United States. Currently, Missouri is the only state in the union that has not adopted some form of a PDMP and lawmakers in Missouri are planning to file legislation in this year's session in order to finally establish a PDMP in their state.

In a 2018 speech, Missouri Governor Mike Parson stated, "[w]e're the only state in the United States that doesn't have [a PDMP]...people are losing their lives every day from a terrible situation. And we've got to figure out to make sure we have all the tools everybody needs to be able to fight that" (Parsons, in Bott, 2018). Parsons is correct that people every day are suffering from overdose deaths—in Missouri, at a rate of over two people per day (CDC Wonder, 2018). However, I find no evidence to suggest that PDMP implementation would actually result in this desired decrease in deaths.

Therefore, the evidence against the effectiveness of PDMPs provided by this study should be seen as a way to reorient the policymaking community away from this dogmatic reliance on the PDMP as a necessary component of a state's opioid crisis response policy and towards exploring more effective solutions. Millions of taxpayer dollars are spent nationwide on the administration of these programs each year, which do not appear to meet their desired goal of reducing deaths. Policy aimed at addressing the opioid crisis must take into account the prevalence of both prescription and illicit opioids in the present-day United States. In 2017, an estimated 191,218,272 opioid prescriptions were written, at a rate of 58.7 per 100 people in the United States (CDC, 2018). Evidently, many Americans have a demand for opioids and derive benefit from their use. Though restrictions on prescribing may inhibit a user's ability to acquire these drugs through legal means, this demand can rather easily be met by seeking out illicit opioids on the black market.

According to Dr. Robert Shearer, an addictionologist in Springfield, Tennessee, "[t]hese patients [who are cut off from legal prescribing channels] are going to have a physical dependency, and some of them might be able to wean themselves off, but some are going to buy heroin on the street and some of that is going to be laced with fentanyl" (Shearer, in Kelman, 2018). As noted by Shearer, drugs purchased on the black market are far more dangerous than those prescribed legally, due to a consumer's lack of information about the true contents of the substance. Thus, restrictions on prescribing—though well intended—seem to be making opioid use *more* dangerous, as users are pushed to underground markets to meet their demand. The findings of this study suggest that this unforeseen substitution to illegally purchased heroin is the principal reason why the PDMP is ultimately ineffective at reducing total overdose deaths, as PDMPs cut off users from legal channels of prescribing and force them to switch to more dangerous illicit drugs.

One policy channel that may have more success in reducing deaths is the expansion of access to health insurance, specifically through Medicaid expansion. In Chapter VI, I find evidence suggesting Medicaid expansion is associated with a 32.1% average reduction in the Heroin Death Rate. Additionally, I identify a statistically, significant, positive relationship between the rate of uninsured and the Synthetic Opioid Death Rate, as well as weaker evidence of a positive relationship between the rate of uninsured and the Total Opioid Death Rate—indicating that a lack of access to healthcare is associated with increased overdose deaths.

Increasing health insurance coverage allows more people to access opioid prescriptions through legal means, thus mitigating users' need to acquire opioids on the more dangerous black market (Chet et al., 2019). Additionally, increased access to insurance expands coverage for Medically Assisted Treatments, such as buprenorphine and methadone—those opioids which help to treat addiction (Volkow et al., 2014).

Contrary to the Standard Narrative's assertion that increased prescribing will lead to more overdose deaths, these findings suggest that expanding access to healthcare, and thus legally prescribed treatments, can work to decrease overdose deaths. Critically, what distinguishes this policy channel from more restrictive means of addressing the opioid crisis—like the PDMP—is that it actually accounts for the high demand for opioids among the American public and works to reduce the harm of opioid use, given this demand. Instead of cutting people off from legal channels of prescribing, as PDMPs do, policies such as Medicaid expansion increase access to legally prescribed opioids and addiction therapy treatments, subduing the need to seek out more dangerous illicit opioids on the black market.

In times of crisis, it is common for lawmakers to rush to identify solutions to address the immediate issue facing the nation. The opioid crisis in the United States is certainly one that needs to be tackled quickly, as tens of thousands of Americans continue to die from opioid overdoses each year. In following the logic of the commonly cited Standard Narrative—which is widely accepted among mainstream government agencies like the CDC—the PDMP ostensibly appears to be an appropriate policy tool that can be readily applied to curb opioid overdose deaths by reducing prescribing. Thus, it is not surprising that states quickly gravitated towards PDMPs and nearly universally implemented them over the last two decades. However, the findings of this study should seriously call into question the effectiveness of PDMPs and suggest that hasty intervention can have grave unintended consequences—which work to contribute to, rather than combat, the crisis.

Bibliography

2015 Annual Review of Prescription Monitoring Programs. Report. National Alliance for Model State Drug Laws (NAMSDL). September 2015. Accessed March 12, 2019. http://www.namsdl.org/library/1810E284-A0D7-D440-C3A9A0560A1115D7/.

Abadie, Alberto, Susan Athey, Guido W. Imbens, and Jeffrey Woolridge. *When Should You Adjust Standard Errors for Clustering?* Working paper no. 24003. National Bureau of Economic Research. Cambridge, MA: NBER, 2017.

"ACS Tables for Health Insurance Coverage." Census Bureau Facts. August 16, 2018. Accessed March 05, 2019. https://www.census.gov/data/tables/time-series/demo/health-insurance/acs-hi.html.

Adams, Jerome. "Surgeon General's Advisory on Naloxone and Opioid Overdose." SurgeonGeneral.gov. 2018. Accessed March 06, 2019. https://www.surgeongeneral.gov/priorities/opioid-overdose-prevention/naloxone-advisory.html.

Adams, Nancy J., Mary Beth Plane, Michael F. Fleming, Marlon P. Mundt, Laura A. Saunders, and Ellyn A. Stauffacher. "Opioids and the Treatment of Chronic Pain in a Primary Care Sample." *Journal of Pain and Symptom Management* 22, no. 3 (2001): 791-96. doi:10.1016/s0885-3924(01)00320-7.

Aitken, H. G. J., and Calvin B. Hoover. "The Economy, Liberty and the State." *The Economic History Review* 13, no. 1 (1960): 171. doi:10.2307/2591451.

Allen, Greg, and Amita Kelly. "Trump Administration Declares Opioid Crisis A Public Health Emergency." NPR. October 26, 2017. Accessed March 05, 2019. https://www.npr.org/2017/10/26/560083795/president-trump-may-declare-opioid-epidemic-national-emergency.

Ayres, Ian, and Amen Jalal. "The Impact of Prescription Drug Monitoring Programs on U.S. Opioid Prescriptions." *The Journal of Law, Medicine, and Ethics*, July 17, 2018. Accessed March 5, 2019. doi:10.2139/ssrn.3165524.

Baldini, Angee, Michael Von Korff, and Elizabeth H. B. Lin. "A Review of Potential Adverse Effects of Long-Term Opioid Therapy." *The Primary Care Companion For CNS Disorders*, June 14, 2012. doi:10.4088/pcc.11m01326.

Benson, Bruce L., and David W. Rasmussen. "Relationship Between Illicit Drug Enforcement Policy And Property Crimes." *Contemporary Economic Policy* 9, no. 4 (December 1991): 106-15. Accessed March 5, 2019. doi: 10.1111/j.1465-7287.1991.tb00354.x.

Benson, Bruce L., Iljoong Kim, David W. Rasmussen, and Thomas W. Zhehlke. "Is Property Crime Caused by Drug Use or by Drug Enforcement Policy?" *Applied Economics* 24, no. 7 (July 1992): 679-92. Accessed March 5, 2019. doi:10.1080/00036849200000036.

Berkson, Joseph. "A Statistically Precise and Relatively Simple Method of Estimating the Bioassay with Quantal Response, Based on the Logistic Function." *Journal of the American Statistical Association* 48, no. 263 (1953): 565. Accessed March 5, 2019. doi:10.2307/2281010.

Bott, Celeste. "Parson Calls for a 'long Overdue' Statewide Prescription Drug Monitoring Program during St. Louis Visit." Stltoday.com. December 06, 2018. Accessed March 11, 2019. https://www.stltoday.com/news/local/crime-and-courts/parson-calls-for-a-long-overdue-statewide-prescription-drug-monitoring/article_c5dda0b4-7be1-55ed-9215-227aadd3349f.html.

Brady, Joanne E., Hannah Wunsch, Charles Dimaggio, Barbara H. Lang, James Giglio, and Guohua Li. "Prescription Drug Monitoring and Dispensing of Prescription Opioids." *Public Health Reports* 129, no. 2 (2014): 139-47. doi:10.1177/003335491412900207.

Brown, Richard, Moira R. Riley, Lydia Ulrich, Ellen Percy Kraly, Paul Jenkins, Nicole L. Krupa, and Anne Gadomski. "Impact of New York Prescription Drug Monitoring Program, I-STOP, on Statewide Overdose Morbidity." *Drug and Alcohol Dependence* 178 (September 1, 2017): 348-54. Accessed March 5, 2019. doi:10.1016/j.drugalcdep.2017.05.023.

Buchmueller, Thomas C., and Colleen Carey. *The Effect of Prescription Drug Monitoring Programs on Opioid Utilization in Medicare*. Report. National Bureau of Economic Research. 23148th ed. Cambridge, MA: NBER, 2017.

"Calculation Total Daily Dose of Opioids for Safer Dosage." Accessed March 5, 2019. https://www.cdc.gov/drugoverdose/pdf/calculating_total_daily_dose-a.pdf.

Case, Anne, and Angus Deaton. *Mortality and Morbidity in the 21st Century.* Working paper. Brookings Institution. Brookings Papers on Economic Activity. Washington, DC: Brookings, 2017.

"CDC Wonder." *Multiple Cause of Death Data*, 2018. Accessed March 5, 2019. CDC Wonder.

Cheatle, Martin D., Rollin M. Gallagher, and Charles P. O'Brien. "Low Risk of Producing an Opioid Use Disorder in Primary Care by Prescribing Opioids to Prescreened Patients with Chronic Noncancer Pain." *Pain Medicine* 19, no. 4 (April 1, 2017): 764-73. doi:10.1093/pm/pnx032.

Cher, Benjamin A.y., Nancy E. Morden, and Ellen Meara. "Medicaid Expansion and Prescription Trends." *Medical Care* 57, no. 3 (March 2019): 208-12. Accessed March 5, 2019. doi:10.1097/mlr.0000000000001054.

"CMS." Opioid Oral Morphine Milligram Equivalent (MME) Conversion Factorsi,i. https://www.cms.gov/Medicare/Prescription-Drug-Coverage/PrescriptionDrugCovContra/Downloads/Oral-MME-CFs-vFeb-2018.pdf.

Coffey, Thomas M. *The Long Thirst: Prohibition in America, 1920- 1933.* London, 1976.

Cowan, David T., Laurie G. Allan, Susan E. Libretto, and Peter Griffiths. "Opioid Drugs: A Comparative Survey of Therapeutic and "Street" Use." *Pain Medicine* 2, no. 3 (2001): 193-203. doi:10.1046/j.1526-4637.2001.01026.x.

"Crime Type." Bureau of Justice Statistics (BJS). Revised March 10, 2019. Accessed March 11, 2019. https://www.bjs.gov/index.cfm?ty=tp&tid=3.

Dave, Dhaval, Monica Deza, and Brady P. Horn. *Prescription Drug Monitoring Programs, Opioid Abuse, and Crime*. Report no. 24975. National Bureau of Economic Research. Cambridge, MA: NBER, 2018.

"DEA ARCOS." ARCOS Retail Drug Summary Reports. Accessed March 05, 2019. https://www.deadiversion.usdoj.gov/arcos/retail_drug_summary/index.html.

Dee, Thomas S. "State Alcohol Policies, Teen Drinking and Traffic Fatalities." *Journal of Public Economics* 72, no. 2 (1999): 289-315. doi:10.1016/s0047-2727(98)00093-0.

"Definition of Moral Hazard | What Is Moral Hazard ? Moral Hazard Meaning." The Economic Times. 2019. Accessed March 06, 2019. https://economictimes.indiatimes.com/definition/moral-hazard.

Delcher, Chris, Yanning Wang, Alexander C. Wagenaar, Bruce A. Goldberger, Robert L. Cook, and Mildred M. Maldonado-Molina. "Prescription and Illicit Opioid Deaths and the Prescription Drug Monitoring Program in

Florida." *American Journal of Public Health* 106, no. 6 (2016). Accessed March 5, 2019. doi:10.2105/ajph.2016.303104.

Dellemijn, Paul L.i. "Opioids in Non-cancer Pain: A Life-time Sentence?" *European Journal of Pain* 5, no. 3 (2001): 333-39. doi:10.1053/eujp.2001.0240.

Deza, Monica, and Brady P. Horn. *The Effect of Prescription Drug Monitoring Programs on Crime*. Working paper. 2017.

Doleac, Jennifer L., and Anita Mukherjee. "The Moral Hazard of Lifesaving Innovations: Naloxone Access, Opioid Abuse, and Crime." *SSRN Electronic Journal*, October 30, 2018. Accessed March 5, 2019. doi:10.2139/ssrn.3135264.

Dowell, Deborah, Rita K. Noonan, and Debra Houry. "Underlying Factors in Drug Overdose Deaths." *JAMA* 318, no. 23 (December 19, 2017). Accessed March 5, 2019. doi:10.1001/jama.2017.15971.

Dunn, Kate M., KW Saunders, CM Rutter, CJ Banta-Green, JO Merrill, MD Sullivan, CM Weisner, MJ Silverberg, CI Campbell, BM Psaty, and M. Von Korff. "Opioid Prescriptions for Chronic Pain and Overdose." *Annals of Internal Medicine* 152, no. 2 (January 19, 2010): 85. Accessed March 5, 2019. doi:10.7326/0003-4819-152-2-201001190-00006.

Englebert, Doug. *WI EPDMP Report*. Report no. 5. Controlled Subtances Board, Wisconsin Department of Safety and Professional Services. 2018.

Evans, William N., Ethan Lieber, and Patrick Power. *How the Reformulation of OxyContin Ignited the Heroin Epidemic*. Working paper no. 24475. National Bureau of Economic Research. Cambridge, MA: NBER, 2018.

"Fentanyl." DEA. 2017. Accessed March 05, 2019. https://www.dea.gov/factsheets/fentanyl.

Fleming, Sara, David P. Rabago, Marlon P. Mundt, and Michael F. Fleming. "CAM Therapies among Primary Care Patients Using Opioid Therapy for Chronic Pain." *BMC Complementary and Alternative Medicine* 7, no. 1 (May 16, 2007). Accessed March 5, 2019. doi:10.1186/1472-6882-7-15.

"FRED." Gross Domestic Product (GDP) by State. Accessed March 05, 2019. https://fred.stlouisfed.org/release?rid=140.

Gelman, Andrew, and Jennifer Hill. *Data Analysis Using Regression and Multilevel/hierarchical Models*. Cambridge: Cambridge University Press, 2007.

Ghertner, Robin, and Lincoln Groves. Report. Office of the Assistant Secretary for Planning and Evaluation, US Department of Health and Human Services.

Gladden, R. Matthew, Pedro Martinez, and Puja Seth. *Fentanyl Law Enforcement Submissions and Increases in Synthetic Opioid–Involved Overdose Deaths — 27 States, 2013–2014*. Report. Centers for Disease Control and Prevention. CDC, 2016.

"Good Samaritan Overdose Prevention Laws." PDAPS. July 1, 2018. Accessed March 5, 2019. http://pdaps.org/datasets/good-samaritan-overdose-laws-1501695153.

Griggs, Christopher, Scott Weiner, and James Feldman. "Prescription Drug Monitoring Programs: Examining Limitations and Future Approaches." *Western Journal of Emergency Medicine* 16, no. 1 (2015): 67-70. doi: 10.5811/westjem.2014.10.24197.

Haffajee, Rebecca L., Anupam B. Jena, and Scott G. Weiner. "Mandatory Use of Prescription Drug Monitoring Programs." *Jama* 313, no. 9 (March 03, 2015): 891. Accessed March 5, 2019. doi:10.1001/jama.2014.18514.

Harold Rogers Prescription Drug Monitoring Program. Bureau of Justice Assistance, US Department of Justice. 2016.

Hedegaard, Holly, Margaret Warner, and Arialdi M. Miniño. *Drug Overdose Deaths in the United States, 1999–2016*. Report. Centers for Disease Control and Prevention. 294th ed. NCHS Data Brief. CDC, 2017.

Higgs, Robert. *Crisis and Leviathan*. New York: Oxford University Press, 1987.

Hildreth, Randi, and Bryan Henry. "Montgomery Doctor Arrested in Pill Mill Case among State's Highest Prescribers." Http://www.wsfa.com. August 09, 2018. Accessed March 05, 2019. http://www.wsfa.com/story/38850939/montgomery-doctor-arrested-in-pill-mill-case-among-states-highest-prescribers/.

History of Prescription Drug Monitoring Programs. Report. The Heller School for Social Policy and Management, Brandeis University. Waltham, MA: PDMP TTAC, 2018.

Horwitz, Jill, Corey S. Davis, Lynn S. McClelland, Rebecca S. Fordon, and Ellen Meara. *The Problem of Data Quality in Analyses of Opioid Regulation: The Case of Prescription Drug Monitoring Programs*. Working paper no.

24947. National Bureau of Economic Research. NBER Working Paper. Cambridge, MA: NBER, 2018.

"Improve Opioid Prescribing." Centers for Disease Control and Prevention. August 30, 2017. Accessed March 05, 2019. https://www.cdc.gov/drugoverdose/prevention/prescribing.html.

Islam, M. Mofizul, and Ian S. Mcrae. "An Inevitable Wave of Prescription Drug Monitoring Programs in the Context of Prescription Opioids: Pros, Cons and Tensions." *BMC Pharmacology and Toxicology* 15, no. 1 (August 16, 2014). Accessed March 5, 2019. doi:10.1186/2050-6511-15-46.

Jones, Mark R., Omar Viswanath, Jacquelin Peck, Alan D. Kaye, Jatinder S. Gill, and Thomas T. Simopoulos. "A Brief History of the Opioid Epidemic and Strategies for Pain Medicine." *Pain and Therapy* 7, no. 1 (April 24, 2018): 13-21. doi:10.1007/s40122-018-0097-6.

Kane, Sean P. "Equivalent Opioid Calculator." Morphine - Drug Usage Statistics, ClinCalc DrugStats Database. Accessed March 05, 2019. https://clincalc.com/Opioids/.

Kellman, Brett. "As Tennessee Pain Clinics Close, Some Desperate Patients May Switch to Heroin, Experts Say." Commercial Appeal. July 6, 2018. Accessed March 12, 2019. https://www.commercialappeal.com/story/news/2018/07/05/comprehensive-pain-clinic-closures-may-push-tennessee-patients-heroin/760498002/.

Kennedy-Hendricks, Alene, Matthew Richey, Emma E. Mcginty, Elizabeth A. Stuart, Colleen L. Barry, and Daniel W. Webster. "Opioid Overdose Deaths and Florida's Crackdown on Pill Mills." *American Journal of Public Health* 106, no. 2 (2016): 291-97. doi:10.2105/ajph.2015.302953.

Kilby, Angela. *Opioids for the Masses: Welfare Tradeoffs in the Regulation of Narcotic Pain Medications*. Department of Economics, Massachusetts Institute of Technology. 2015.

Livingston, Melvin D., Tracey E. Barnett, Chris Delcher, and Alexander C. Wagenaar. "Recreational Cannabis Legalization and Opioid-Related Deaths in Colorado, 2000–2015." *American Journal of Public Health* 107, no. 11 (November 2017): 1827-829. Accessed March 5, 2019. doi:10.2105/ajph.2017.304059.

Mallat, Justine. *The Effect of Prescription Drug Monitoring Programs on Opioid Prescriptions and Heroin Crime Rates*. Working paper no. 1292. Economics Department, Purdue University. 2017.

Mars, Sarah G., Daniel Rosenblum, and Daniel Ciccarone. "Illicit Fentanyls in the Opioid Street Market: Desired or Imposed?" *Addiction*, October 04, 2018. Accessed March 8, 2019. doi:10.1111/add.14474.

Marshall, Edward. "Uncle Sam Is the Worst Drug Fiend in the World." *The New York Times*, March 12, 1911.

Maryland Advisory Council on Prescription Drug Monitoring Legislative Report. Report. Maryland Advisory Council. December 31, 2009. Accessed March 5, 2019. http://msa.maryland.gov/megafile/msa/speccol/sc5300/sc5339/000113/012000/012478/unrestricted/20100355e.pdf.

Mcclellan, Chandler, Barrot H. Lambdin, Mir M. Ali, Ryan Mutter, Corey S. Davis, Eliza Wheeler, Michael Pemberton, and Alex H. Kral. "Opioid-overdose Laws Association with Opioid Use and Overdose Mortality." *Addictive Behaviors* 86 (November 2018): 90-95. Accessed March 5, 2019. doi:10.1016/j.addbeh.2018.03.014.

Mcmichael, Benjamin J., Ray Van Horn, and W. Kip Viscusi. "The Impact of Cannabis Access Laws on Opioid Prescribing." *SSRN Electronic Journal*, 2018. Accessed March 5, 2019. doi:10.2139/ssrn.3266629.

Meara, Ellen, Jill R. Horwitz, Wilson Powell, Lynn Mcclelland, Weiping Zhou, A. James Omalley, and Nancy E. Morden. "State Legal Restrictions and Prescription-Opioid Use among Disabled Adults." *New England Journal of Medicine* 375, no. 1 (July 07, 2016): 44-53. Accessed March 5, 2019. doi:10.1056/nejmsa1514387.

"Medication-Assisted Treatment (MAT)." Stages of Community Readiness | SAMHSA. July 21, 2015. Accessed March 05, 2019. https://www.samhsa.gov/medication-assisted-treatment.

Miron, Jeffrey A., and Jeffrey Zwiebel. "The Economic Case Against Drug Prohibition." *Journal of Economic Perspectives* 9, no. 4 (1995): 175-92. doi:10.1257/jep.9.4.175.

Miron, Jeffrey A., and Elina Tetelbaum. *Does the Minimum Legal Drinking Age Save Lives?* Working paper no. 13257. National Bureau of Economic Research. NBER Working Paper. Cambridge, MA: NBER, 1999.

Miron, Jeffrey, Greg Sollenberger, and Laura Nicolae. *Overdosing on Regulation: How Government Caused the Opioid Epidemic.* Technical paper no. 864. Cato Institute. Policy Analysis. Washington, DC: Cato Institute, 2019.

Morphine Equivalent Dosing. Report. Wolters Kluwer. RxPerts Industry Insights, 2018.

Musumeci, MaryBeth, and Jennifer Tolbert. "Federal Legislation to Address the Opioid Crisis: Medicaid Provisions in the SUPPORT Act." The Henry J. Kaiser Family Foundation. October 30, 2018. Accessed March 05, 2019. https://www.kff.org/medicaid/issue-brief/federal-legislation-to-address-the-opioid-crisis-medicaid-provisions-in-the-support-act/.

"Naloxone Overdose Prevention Laws." PDAPS. July 1, 2017. Accessed March 05, 2019. http://pdaps.org/datasets/laws-regulating-administration-of-naloxone-1501695139.

National Safety Council Injury Facts. Report. National Safety Council. 0233-0000 ed. Itasca, IL: NSC, 2017.

Noble, Meredith, Jonathan R. Treadwell, Stephen J. Tregear, Vivian H. Coates, Philip J. Wiffen, Clarisse Akafomo, and Karen M. Schoelles. "Long-term Opioid Management for Chronic Noncancer Pain." *Cochrane Database of Systematic Reviews*, January 20, 2007. Accessed March 5, 2019. doi: 10.1002/14651858.cd006605.

"Opioid Overdose Crisis." NIDA. January 22, 2019. Accessed March 05, 2019. https://www.drugabuse.gov/drugs-abuse/opioids/opioid-overdose-crisis.

"Opioid Painkiller Prescribing." CDC. July 2014. Accessed March 05, 2019. https://www.cdc.gov/vitalsigns/opioid-prescribing/index.html.

"Pain & Policy Studies Group." INCB. Accessed March 5, 2019. http://www.painpolicy.wisc.edu/publications.

"Pain Management Clinic Laws." PDAPS. June 1, 2018. Accessed March 5, 2019. http://pdaps.org/datasets/pain-management-clinic-laws.

Paulozzi, Leonard J., Edwin M. Kilbourne, and Hema A. Desai. "Prescription Drug Monitoring Programs and Death Rates from Drug Overdose." *Pain Medicine* 12, no. 5 (2011): 747-54. Accessed March 5, 2019. doi:10.1111/j.1526-4637.2011.01062.x.

"Population." Census Bureau Facts. US Census Bureau. August 21, 2018. Accessed March 05, 2019. https://www.census.gov/topics/population.html.

Portenoy, Russell K., and Kathleen M. Foley. "Chronic Use of Opioid Analgesics in Non-malignant Pain: Report of 38 Cases." *Pain* 25, no. 2 (1986): 171-86. Accessed March 7, 2019. doi:10.1016/0304-3959(86)90091-6.

Rastegar, Darius A. "Prescription Monitoring Program and "Pill Mill" Laws Have Had Modest Effects on Opioid Overprescribing in Florida." November 1, 2015. Accessed March 06, 2019. https://www.bu.edu/aodhealth/2015/11/01/prescription-monitoring-program-and-pill-mill-laws-have-had-modest-effects-on-opioid-overprescribing-in-florida/.

Redford, Audrey, and Benjamin W. Powell. "Dynamics of Intervention in the War on Drugs: The Build-Up to the Harrison Act of 1914." *The Independent Review* 20, no. 4 (Spring 2016). Accessed March 5, 2019. doi:10.2139/ssrn.2533166.

Reisman, Richard M., Pareen J. Shenoy, Adam J. Atherly, and Christopher R. Flowers. "Prescription Opioid Usage and Abuse Relationships: An Evaluation of State Prescription Drug Monitoring Program Efficacy." *Substance Abuse: Research and Treatment* 3 (2009). Accessed March 5, 2019. doi:10.4137/sart.s2345.

Rosenblum, Daniel, George Jay Unick, and Daniel Ciccarone. "The Entry of Colombian-sourced Heroin into the US Market: The Relationship between Competition, Price, and Purity." *International Journal of Drug Policy* 25, no. 1 (January 2014): 88-95. Accessed March 5, 2019. doi: 10.1016/j.drugpo.2013.10.003.

Ross-Degnan, Dennis, Linda Simoni-Wastila, Jeffrey S. Brown, Xiaoming Gao, Connie Mah, Leon E. Cosler, Thomas Fanning, Peter Gallagher, Carl Salzman, Richard I. Shader, Thomas S. Inui, and Stephen B. Soumerai. "A Controlled Study of the Effects of State Surveillance on Indicators of Problematic and Non-Problematic Benzodiazepine Use in a Medicaid Population." *The International Journal of Psychiatry in Medicine* 34, no. 2 (June 1, 2004): 103-23. Accessed March 5, 2019. doi:10.2190/8fr4-qyy1-7myg-2agj.

Rutkow, Lainie, Hsien-Yen Chang, Matthew Daubresse, Daniel W. Webster, Elizabeth A. Stuart, and G. Caleb Alexander. "Effect of Florida's Prescription Drug Monitoring Program and Pill Mill Laws on Opioid Prescribing and Use." *JAMA Internal Medicine* 175, no. 10 (October 2015): 1642-649. Accessed March 5, 2019. doi:10.1001/jamainternmed.2015.3931.

"Sen. Cruz: 'Too Many Lives Have Been Lost to the Opioid Crisis, and Today We Take a Stand for All Americans'." News release, October 3, 2018. US Senator for Texas Ted Cruz. Accessed March 5, 2019. https://www.cruz.senate.gov/?p=press_release&id=4126.

Silverman, Lester P., and Nancy L. Spruill. "Urban Crime and the Price of Heroin." *Journal of Urban Economics* 4, no. 1 (January 1977): 80-103. Accessed March 5, 2019. doi:10.1016/0094-1190(77)90032-8.

Simeone, Ronald, and Lynn Holland. *An Evaluation of Prescription Drug Monitoring Programs*. Report. Simeone Associates, Inc. 2006.

"State Profiles." PDMP TTAC. Accessed March 05, 2019. http://www.pdmpassist.org/content/state-profiles.

"Status of State Action on the Medicaid Expansion Decision." The Henry J. Kaiser Family Foundation. February 13, 2019. Accessed March 05, 2019. https://www.kff.org/health-reform/state-indicator/state-activity-around-expanding-medicaid-under-the-affordable-care-act/.

Stock, James H., and Mark W. Watson. *Introduction to Econometrics*. New York, NY: Pearson, 2014.

Stolz, Claire. *The Effects of Prescription Drug Monitoring Programs on Opioid Use, Disability, and Mortality*. Working paper. Department of Economics, Harvard University. Cambridge, MA, 2016.

Terry, C. E. "The Harrison Anti-Narcotic Act." *American Journal of Public Health* 5, no. 6 (1915): 518. doi:10.2105/ajph.5.6.518.

Thornton, Mark. *Alcohol Prohibition Was a Failure*. Working paper no. 157. Cato Institute. Policy Analysis. Washington, DC: Cato Institute, 1991.

Thornton, Mark. *The Economics of Prohibition*. Salt Lake City: University of Utah Press, 1991.

Turk, Dennis C., Michael C. Brody, and Akiko E. Okifuji. "Physicians' Attitudes and Practices regarding the Long-term Prescribing of Opioids for Non-cancer Pain." *Pain* 59, no. 2 (November 1994): 201-08. Accessed March 5, 2019. doi:10.1016/0304-3959(94)90072-8.

"U.S. Opioid Prescribing Rate Maps." Centers for Disease Control and Prevention. October 03, 2018. Accessed March 11, 2019. https://www.cdc.gov/drugoverdose/maps/rxrate-maps.html.

"UCR Publications." Bureau of Justice Statistics. September 10, 2018. Accessed March 05, 2019. https://www.fbi.gov/services/cjis/ucr/publications.

"Understanding the Epidemic." Centers for Disease Control and Prevention. December 19, 2018. Accessed March 05, 2019. https://www.cdc.gov/drugoverdose/epidemic/index.html.

Using Prescription Drug Monitoring Program Data to Support Prevention Planning. Report. Substance Abuse and Mental Health Services Administration. Accessed March 5, 2019. https://www.samhsa.gov/capt/sites/default/files/resources/pdmp-overview.pdf.

Van Zee, Art. "The Promotion and Marketing of OxyContin: Commercial Triumph, Public Health Tragedy." *American Journal of Public Health* 99, no. 2 (February 2009): 221-27. Accessed March 5, 2019. doi:10.2105/ajph.2007.131714.

Vestal, Christine. "States Require Doctors to Use Prescription Drug Monitoring Systems for Patients." The Washington Post. January 15, 2018. Accessed March 06, 2019. https://www.washingtonpost.com/national/health-science/states-require-doctors-to-use-prescription-drug-monitoring-systems-for-patients/2018/01/12/c76807b8-f009-11e7-97bf-bba379b809ab_story.html?utm_term=.c0f616ed827f.

Volkow, Nora D., Thomas R. Frieden, Pamela S. Hyde, and Stephen S. Cha. "Medication-Assisted Therapies — Tackling the Opioid-Overdose Epidemic." *New England Journal of Medicine*, May 29, 2014, 2063-066. Accessed March 5, 2019.

Whalen v. Roe, 429 U.S. 589 (1977).

"What States Need to Know about PDMPs." Centers for Disease Control and Prevention. October 03, 2017. Accessed March 05, 2019. https://www.cdc.gov/drugoverdose/pdmp/states.html.

Zezima, Abby Goodman. "New OxyContin Formula Is Said to Curb Abuses." The New York Times. June 15, 2011. Accessed March 06, 2019. https://www.nytimes.com/2011/06/16/health/16oxy.html.

Appendix A

Table A1

Variable	N	Min	Median	Mean	Max	Std Dev
Non-Mandatory PDMP	969	0	0	0.24	1	0.41
Mandatory PDMP	969	0	0	0.16	1	0.36
MMEs Per Capita	867	151.5	680.8	721.5	1788.3	345.92
Total Death Rate	969	0.13	5.89	7.44	45.87	5.79
Heroin Death Rate	910	0.02	0.91	1.74	18.3	2.32
Synthetic Death Rate	953	0.02	0.8	1.8	16	3.68
Other Death Rate	967	0.06	2.47	3.183	23.82	2.73
Violent Crime Arrest Rate	948	0.31	114.39	128.45	397.28	70.61
Property Crime Arrest Rate	951	10.14	445.2	438.71	877.61	169.40
Drug Crime Arrest Rate	951	4.54	372.94	391.88	1023.38	176.93
Naloxone Access	969	0	0	0.2	1	0.39
Pill Mill Laws	969	0	0	0.079	1	0.26
Good Samaritan Laws	969	0	0	0.16	1	.35
Medicaid Expansion	969	0	0	0.122	1	.33
Percent Uninsured	969	2.4	11.7	12.12	24.6	4.23
State GDP per Capita	969	22566	43543	47229	195639	19647.92
State Unemployment Rate	969	2.3	5.2	5.64	13.6	1.97
MML	969	0	0	0.297	1	0.46
RML	969	0	0	0.03	1	0.17
Agencies Reporting	951	1	173	240.1	1383	225.25

Table A1 reports the descriptive statistics of sample size, minimum vale, median value, average, maximum value, and standard deviation for the variables described in Chapter IV and used in the models in Chapters V, VI, and VII.

Appendix B

For access to the originally compiled dataset used in this thesis, please visit the following web address:

https://scholar.harvard.edu/capodilupo/publications/data-companion-combatting-or-contributing-crisis-evaluating-effectiveness