Medicaid Expansion and the Opioid Epidemic: How does increasing health insurance impact the crisis?

Mark McInerney
University of Connecticut
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Abstract:

This study examines the impact of expanded health insurance coverage, resulting from the Patient Protection and Affordable Care Act of 2010, on opioid related mortality. These effects are identified using variation in the expansion of Medicaid across states and over time. Opioid related mortality data from 1999-2016 were obtained from the Centers for Disease Control and Prevention. My findings suggest the implementation of Medicaid expansion resulted in about a 29% reduction in heroin deaths and a 14% increase in methadone deaths. These findings build on recent work that shows increases in specialty treatment utilization and increases in prescriptions use to treat substance use disorders in expanding states.

1. Introduction

In 2017, about 130 Americans died as a result of an opioid overdose per day (CDC, 2018). Keith Humphreys, an addiction specialist at Stanford, recently said: "…even if you ignored deaths from all other drugs, the opioid epidemic alone is deadlier than the AIDS epidemic at its peak" (Ingraham, 2017). As the crisis has unfolded, the Patient Protection and Affordable Care Act (ACA) of 2010 began a dramatic reshaping of the American health care system. Integral to the law was expansion of health insurance access and more robust requirements for coverage of mental health and substance use disorder (SUD) treatments.

The role of the American medical system in contributing to the opioid epidemic raises important questions about individuals who gained health insurance coverage and misuse of opioids. I consider two channels through which the expansion of health insurance may impact the opioid epidemic: increased access to treatment for opioid use disorder (OUD) and increased access to prescription opioids. This study fills a gap in the literature by examining each subcategory of opioid related mortality available from the Centers for Disease Control and Prevention (CDC) multiple cause of death file. I use a difference-in-differences model to estimate the causal impact of public health insurance expansion resulting from the ACA on opioid overdose deaths by using variation in Medicaid expansions across states and over time. I find that the Medicaid expansions led to decreases in heroin related overdose deaths and increases in methadone related overdose deaths. Understanding these effects is of particular importance given recent legislative proposals to alter or repeal the ACA and the increasing severity of the opioid epidemic.

Because the expansion of Medicaid may have both positive and negative impacts on opioid related deaths, I examine each type of opioid mortality individually. Using this disaggregation approach, I attempt to disentangle the effects of the Medicaid expansions on opioids that Medicaid may fund (opioid analgesics, methadone, etc.) and opioids that Medicaid will not fund (heroin, illicit fentanyl, ect.). If the Medicaid expansions impact opioid related mortality in both directions, the effects may only be statistically detectable when looking at individual categories of cause of death.

2. Policy Background

One of the primary goals of the ACA was to increase access to health care for the large number of uninsured individuals in the U.S. Toward this goal, the ACA increased the minimum income requirement for Medicaid coverage to 138% of the federal poverty level. As a result of a 2012 Supreme Court decision, the decision to expanded Medicaid was left to states. 36 states and Washington D.C. have adopted the Medicaid expansion to date (KFF, 2019).[1] The uninsured rate among the non-elderly population has decreased from 18.2% in 2010 to 10.5% in 2015 (KFF, 2017). Medicaid enrollment has increased by 26% nationally (KFF, 2018). Policy uncertainty has surrounded the ACA including multiple attempts to repeal the law and the successful repeal of the individual mandate in 2017. This policy uncertainty may have undermined potential public health benefits of the ACA by discouraging investment in health care infrastructure, discouraging potential beneficiaries and causing some insurers to leave the marketplace.

The ACA required states that expanded Medicaid to offer Alternative Benefit Plans (ABP) to the newly eligible expansion population. ABPs were required by law to cover ten essential health benefits including treatment for SUDs (Grogan et al., 2016). The ACA does not

[1] In some cases, the expansion of Medicaid has been adopted but not implemented.

specify which SUD treatment services must be offered. As of October 2017, over 74 million individuals were enrolled in Medicaid (Centers for Medicare & Medicaid Services, 2017). Overall, about 12% of adult Medicaid beneficiaries have a SUD (Center for Medicaid and CHIP Services, 2015). Bachrach et al. (2016) write: "The expansion population—largely single adults not traditionally covered under Medicaid before the ACA—has a higher prevalence of SUDs than populations previously eligible for Medicaid." It is estimated that 1.6 million individuals with SUDs received health benefits as a result of the Medicaid expansions (Grogan et al., 2016).

Medicaid is the largest source of funding for behavioral health treatment in the U.S. (Bachrach et al., 2016). For patients with SUDs, most outcomes improve with admission to treatment compared to those that don't seek treatment: decreases in drug use, decreases in criminal activity and improvements in social and occupational outcomes (National Institute on Drug Abuse, 2012). The American Society of Addiction Medicine (ASAM) guidelines for treatment of OUD recommend that psychosocial treatment be used in concurrence with OUD medications (Grogan et al., 2016). Such treatments (both impatient and outpatient) and medications can be prohibitively costly for the uninsured.

2.1 Mechanisms

Of particular concern in this study is the impact of access to health care (though insurance) on misuse of opioids. Many current opioid users were first introduced to opioids via legal medical channels. Cicero et al. (2014) find that among heroin users entering treatment, 75% of users' first opioid use came in the form of a prescription opioid and by 2010, 94% of users' selected heroin because prescription opioids were becoming too expensive and/or hard to obtain. It is increasingly evident that opioids obtained through the American medical system have been misused by recipients and have been diverted from the medical market to the illegal non-medical market. Powell et al. (2016) study the introduction of Medicare Part D and find that a 10% increase in access to medical opioids led to a 14.1% increase in SUD treatment admissions and a 7.4% increase in opioid deaths. Expanding Medicaid coverage may increase the supply and decrease the cost of prescription opioids (including OUD medications) in a given area. Through this channel, increasing health insurance coverage may lead to misuse of opioids (analgesics, illicit opioids or OUD medications).

The FDA has approved three medications to treat OUD: methadone, buprenorphine, and naltrexone. These medications are used to relieve opioid withdrawal symptoms and can be used safely over long periods of time (months or years). Buprenorphine is the most commonly prescribed OUD medication (Wen et al., 2017). Medication Assisted Treatment (MAT) has been shown to increase patient survival and patient retention in treatment, decrease opioid misuse and improve other outcomes (SAMHSA, 2015). However, FDA approved OUD medications can lead to overdose death. There were 66,592 methadone related overdose deaths in the U.S. from 1999-2016 (CDC Wonder, ICD-10 code T40.3 Methadone, 2018). The rate of methadone related overdose death per 100,000 increased by 600% from 1999-2014 (Faul et al., 2017). Methadone carries significant risk of overdose as it provides pain relief for about 4-8 hours but stays in the body for up to 59 hours (FDA, 2006). Methadone can slow breathing and affect heartbeat. Misuse of methadone can occur when patients take higher doses than recommended, take doses too frequently, obtain multiple prescriptions or obtain methadone on the black market. Methadone may be prescribed and administered under supervision or patients may be given take-home doses. Methadone misuse and diversion are particularly problematic with respect to take-home doses (SAMHSA, 2015). The chief medical officer for Medicaid in West Virginia, Dr. James Becker stated: “If you use methadone responsibly and everyone is playing by the rules, it's a safe medication and it's effective…But if you're not playing by the rules, it gets out onto the street and people die. It has a dual personality" (Vestal, 2015). Misuse of methadone may be particularly problematic among Medicaid beneficiaries. Faul et al. (2017) find that in 2014, the methadone prescribing rate for Medicaid enrollees was about double that of Commercial Claims and Encounters enrollees.

Recent studies have found significant increases in admissions to specialty treatment and prescriptions for medication use to treat SUD in expanding states relative to non-expanding states. Meinhofer and Witman (2018) show that aggregate treatment admissions for OUD increased by 18% in expanding states. Among Medicaid beneficiaries, opioid related admissions increased by 113% in expanding states without crowding out beneficiaries of other insurance types (Meinhofer and Witman, 2018). Maclean and Saloner (2019) find that Medicaid coverage increased among patients receiving specialty treatment and Medicaid payments for specialty treatment increased within expanding states. Further, the volume of prescriptions approved by the FDA to treat SUD increased in expanding states (Maclean and Saloner, 2019). Wen et al. (2017) find that the expansion of Medicaid in 2014 led to a 70% increase in buprenorphine prescriptions covered by Medicaid and a 50% increase in Medicaid spending on buprenorphine. Saloner et al. (2018) look across all payers (public, private and cash) and find that buprenorphine with naloxone prescriptions increased by about 13% within counties that expanded Medicaid.

Patient access to MAT is limited in a number of ways. Cost is an important barrier for the uninsured population. A full course of buprenorphine maintenance costs about $6,000 per patient per year (Wen et al., 2017) while the cost of methadone maintenance is about $4,700 per patient per year (National Institute on Drug Abuse, 2012). Medicaid benefits vary across states and may not cover both medications. From 2004-2013, the number of states in which Medicaid benefits cover both methadone and buprenorphine increased from 21 states to 32 states (Burns et al., 2016). Beyond cost, MAT is limited by physician waivers under the Drug Addiction Treatment Act of 2000. In order to prescribe FDA approved opioids to treat OUD, physicians must apply with the Substance Abuse and Mental Health Services Administration (SAMHSA) for a waiver (Jones et al., 2015). Initially, those physicians receiving the waiver can prescribe to up to 30 patients and up to 100 after one year and with a revised waiver (Jones et al., 2015). Despite these patient limits, approximately 44-66% of physicians with the waiver do not prescribe buprenorphine at all (Jones et al., 2015).

There are many other barriers to receiving treatment. These barriers include lack of individual desire to stop using, a lack of awareness of treatment options or a lack of awareness of the need for treatment (Center for Behavioral Health Statistics and Quality, 2016). Among the population of patients aware of the need for treatment, there are other obstacles including strong social stigma, waiting lists for admission to treatment, language barriers, transportation barriers and others. Only a small percentage of the total population with a SUD receives treatment in a given year, about one out of ten (Center for Behavioral Health Statistics and Quality, 2016). An estimated 20.2 million adults in the U.S. had a SUD in 2014 (Lipari and Van Horn, 2017).

2.2 The Opioid Epidemic

The opioid epidemic is part of a broader public health crisis in the U.S. Case and Deaton (2015) show that despite longstanding declining mortality rates, there was an increase in mortality rates for US White non-Hispanics ages 45-55 between 1990 and 2010. Increasing mortality rates were driven by increases in drug and alcohol poisonings and suicide (Case and Deaton, 2015). Pain killers were traditionally prescribed for short-term use, post-surgery pain, and for pain related to life threatening or terminal illnesses. In 1980, a letter to the editor in the

New England Journal of Medicine noted that patients rarely become addicted to narcotic pain killers (Gounder, 2013). A 1986 study published in the Journal of Pain concluded that, for non-cancer pain, narcotics: “can be safely and effectively prescribed to selected patients with relatively little risk of producing the maladaptive behaviors which define opioid abuse” (Gounder, 2013).

Purdue Pharma began manufacturing OxyContin in 1996 and started to encourage doctors to prescribe pain killers more frequently. Kolodny et al. (2015) state: “Between 1996 and 2002, Purdue Pharma funded more than 20,000 pain-related educational programs through direct sponsorship or financial grants and launched a multifaceted campaign to encourage long-term use of OPRs [Opioid Pain Relievers] for chronic non-cancer pain”. By 2010, OxyContin was the 15th ranked prescription by retail sales (Alpert et al., 2018). OxyContin became over-prescribed and widely available in the US. Some studies have identified OxyContin as one of the causes of the opioid epidemic (Kolodny et al., 2015).

Many policies and interventions intended to curb the opioid epidemic have focused on the supply of opioids (Alpert et al., 2018). Recent research has shown that some policies focusing on the supply of prescription opioids have had the unintended consequence of leading opioid users to substitute across different types of opioids. Persistent misuse of OxyContin led Purdue Pharma to reformulate the drug in 2010. OxyContin was typically misused by crushing pills and then injecting or inhaling (Alpert et al., 2018). Purdue Pharma introduced a pill that was harder to crush and abuse. Evans et al. (2019) find that the rapid increase in heroin related overdose deaths began the month after abuse-deterrent OxyContin was introduced. Alpert et al. (2018) focus on the geographic variation in the prevalence of OxyContin misuse prior to the introduction of abuse-deterrent OxyContin. The authors find that one additional percentage point of OxyContin misuse was associated with 2.5 additional heroin deaths per 100,000 (Alpert et al., 2018).

Many states have responded to the opioid epidemic with legislation in different forms. Prescription Drug Monitoring Programs (PDMPs) established centralized, electronic databases designed to curb overprescribing. PDMPs can regulate over-prescription resulting from prescriber behavior and patient behavior. Evidence regarding the effectiveness of PDMPs and other policies that sought to curb excessive opioid prescribing has been mixed. Bao et al. (2016) find that enacting a PDMP was associated with about a 30% reduction in the prescribing rate of Schedule II opioid painkillers. Kilby (2015) shows that PDMPs reduced opioid related overdose deaths but were also associated with substitution from prescription opioids to heroin. Buchmueller and Carey (2018) find that PDMPs have not affected prescribing rates unless they included “must access” clauses, which the majority of PDMPs do not have. In some states, pain clinics provided large quantities of opioid analgesics, often with little oversight or medical justification (Dowell et al., 2016). 11 states have passed Pain Clinic Laws (PCLs) to establish additional regulation and oversight over opioid prescribing. Dowell et al. (2016) find that the implementation of PCLs along with PDMPs with mandated provider review decreased opioid prescribing rates and opioid related death rates.

Naloxone (also known by the brand name Narcan) is a substance that can block or reverse the effects of opioids in the case of an overdose. Naloxone Access Laws (NALs) make it easier for medical professionals to prescribe and distribute Naloxone. Good Samaritan Laws (GSLs) remove criminal liability for persons seeking to help a person in danger. Opioid overdose deaths are generally not sudden, bystanders able to recognize an overdose can seek medical care and help prevent overdose deaths (Rees et al., 2017). Rees et al. (2017) study the impact of GSLs and NALs on opioid related mortality and find that the adoption of NALs was associated with a 9-11% reduction in opioid-related deaths. The availability of medical marijuana may also impact opioid use. For example, in states where medical marijuana is accessible, marijuana may be prescribed for chronic pain instead of opioid analgesics. Bachhuber et al. (2014) find that states that passed MMLs had about a 25% lower mean annual opioid related death rate.

3. Data

The primary outcome variable used in this study is opioid related mortality. These data were obtained from the CDC Wide-ranging online data for epidemiologic research (Wonder) multiple cause-of-death detailed mortality files. This sample includes data from 1999-2016 at the state, year level. Following Rees et al. (2017), I classify all opioid related overdose deaths by *International Classification of Disease*, *Tenth Revision* (ICD-10) codes as including: T40.0 (opium), T40.1 (heroin), T40.2 (other opioids), T40.3 (methadone), T40.4 (other synthetic narcotics) and T40.6 (other/unspecified narcotics). I consider each of these categories as individual outcome variables (excluding opium due to the low number of deaths associated with opium). Additionally, I consider ICD-10 code: T50.9 (other and unspecified drugs, medicaments and biological substances) which is discussed in more detail in section 6.1. These data include underlying cause of death codes: X40-X44 (Unintentional), X60-X64 (Suicide), X85 (Homicide) and Y10-Y14 (Undetermined). It should be noted that any one overdose death could involve multiple ICD-10 codes (for example, heroin and other opioids were both used by an individual that later died). I apply the same classifications to county, year level data (2003-2016). Mortality data with county level identifiers were obtained from The National Association for Public Health Statistics and Information Systems (NAPHSIS).

Second, I consider outcomes from the Centers for Medicare & Medicaid Services State Drug Utilization data. I examine data from 2006-2016 containing methadone prescriptions reimbursed by Medicaid at the state, quarterly level. I test three outcomes: number of prescriptions, Medicaid amount reimbursed and units reimbursed. Medicaid State Drug Utilization data separates prescriptions by utilization type (fee for service or managed care) and by product code. I aggregate the data to state, quarterly level observations as follows:

$$Prescription_{s,t} = \sum_{i,j} Y_{i,j,s,t} \qquad (1)$$

Where $Y_{i,j,s,t}$ is the number of prescriptions of product code *i*, of utilization type *j*, in state *s*, in quarter *t*.

I control for other changes in state law designed to alleviate the opioid epidemic or that may impact outcomes related to the opioid epidemic. These laws include NALs, GSLs, PDMPs (including earlier substances monitoring programs), PDMPs with a must access clause, PCLs and MMLs (hereafter referred to as other pertinent laws). The effective dates and classification of these laws is listed in table A1. Controlling for such changes in state law can eliminate any potential confounding impact resulting from policy change unrelated to the Medicaid expansions. Data regarding the implementation dates of NALs and GSLs comes from Rees et al. (2017) and the Policy Surveillance Program (2018). The effective dates of PDMPs come Kilby (2015) and the National Alliance for Model State Drug Laws (2018). Classification and dates of PDMPs with a "must access" clause come from Buchmueller and Carey (2018). Implementation dates of MMLs come from Baggio et al. (2018). Effective dates of PCLs were derived from Meinhofer and Witman (2018). Medicaid expansion dates come from the Kaiser Family Foundation (KFF) and Maclean and Saloner (2019). Unemployment data was obtained from the Bureau of Labor

Statistics (state and county level). Population and demographic data (state and county level) come from the National Center for Health Statistics (NCHS) Bridged-Race Population Estimates. Demographic controls include the fraction of the state or county population that is female, white, black, ages 0-15, ages 16-35 and ages 36-64. State quarterly level population data were obtained from the Bureau of Economic Analysis Personal Income Summary.

4. Identification Strategy

I apply a difference-in-differences (DD) empirical strategy. Specifically, I estimate the following Poisson regression:

$$\ln(\lambda_{s,t}) = \beta_1 + \beta_2\, Medicaid_{s,t} + X_{s,t}\,\gamma + \delta_t + \mu_s + + \varepsilon_{s,t} \qquad (2)$$

The outcome of interest, $\lambda_{s,t}$, is the number of opioid related deaths in state *s* in year *t*. $X_{s,t}$ is a vector of controls including, the natural log of the state population, the state unemployment rate, state demographics (age, gender and race) and other pertinent laws. δ_t is the year fixed effect, which will capture the aggregate time trends. μ_s is the state fixed effect. β_2 is the coefficient of interest, capturing the impact of the Medicaid expansions on opioid related mortality. $Medicaid_{s,t}$ is an indicator variable equal to 1 if the expansion of Medicaid was in effect in state *s* and year *t* ($Medicaid_{s,t}$ is a fraction if in place for a portion of that year and equal to 0 otherwise). Equation 2 is weighted by total population at the state, year level. Standard errors are adjusted for clustering at the state level.

Of particular concern is the definition of treatment and control in the DD specification. Previous Medicaid expansions along with differences among the early expanding states could confound the treatment effect (Kaestner et al., 2017). Five states and Washington D.C. expanded Medicaid prior to January 1st 2014: CA, CT, D.C., MN, NJ and WA. Within the early expanding states, many Medicaid enrollees did not gain insurance; rather, they were shifted from county or state level programs resulting from earlier Medicaid expansions (KFF, 2012). CA and CT did experience large increases in enrollment following early expansion (KFF, 2012). For this reason, CA and CT are the only states among the early expanding states included in my primary specification while D.C., MN, NJ and WA are dropped. I consider a number of alternate specifications to test the sensitivity of findings to the definition of treatment and control groups (see section 5.1 for additional discussion).

Using survey data from Burns et al. (2016), I estimate a model that takes into account differences in Medicaid benefits across states and over time. Using this model, I may more accurately identify the treatment effect (expansion of Medicaid) with respect to access to OUD medications. This specification is particularly pertinent when estimating models where methadone related deaths or methadone prescriptions are the dependent variable and when considering the channel of access to MAT for OUD. I estimate the following equation:

$$\ln(\lambda_{s,t}) = \beta_1 + \beta_2\, Medicaid_{s,t} * MAT_{s,t} + \beta_3\, Medicaid_{s,t} * OtherStates_{s,t} + X_{s,t}\gamma + \delta_t + \mu_s + \varepsilon_{s,t} \qquad (3)$$

Here, $MAT_{s,t}$ is an indicator variable equal to 1 if buprenorphine and methadone are covered by Medicaid in state *s* and year *t* (equal to zero otherwise). $Medicaid_{s,t} * OtherStates_{s,t}$ captures the impact of the expansion of Medicaid in states in which Medicaid benefits do not cover both buprenorphine and methadone.

The validity of this identification strategy relies on satisfaction of the common trends assumption. I test this assumption using event study analysis. The event studies are limited in terms of post period data as the majority of expanding states expanded Medicaid in 2014 or later.

With respect to 2014 expanding states, the data contain 3 total years of event year/post policy period data (2014, 2015 and 2016). In specifications including CA and CT, additional post policy period data is available. I estimate the following event study model:

$$\ln(\lambda_{s,t}) = \alpha + (\sum_{t=-5}^{3+} ES_{s,t})\,\beta + X_{s,t}\,\gamma + \delta_t + \mu_s + + \varepsilon_{s,t} \qquad (4)$$

Where $ES_{s,t}$ is an indicator variable equal to one in treatment state s, in year t in relation to the policy change. I begin the event study 5 years prior to the policy change and group all observations 3 or more years after the policy change.[2] I also estimate event studies in which all early and late expanding states are dropped.

My primary specification uses state, year level data. I present Poisson results as my primary specification because the dependent variable of interest is a count. [3] I examine the robustness of these results to use of county, year level data and to different distributional assumptions about the outcome variable. I convert the outcome variable to a rate of opioid related mortality per 100,000 in state s and in year t to estimate OLS models (including the same controls except the log population control). The death rate is transformed using the natural log (LN) or inverse hyperbolic sine (IHS) functions.[4] Prior to the log transformation, I add 1 to the death rate per 100,000 to prevent missing observations.

5. Results

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[2] I have also run event studies grouping all pre-treatment years 5 years or more prior to treatment. Event studies appear similar in these specifications in terms of pre-trend analysis.
[3] In a few instances, I force Poisson models to converge after 500 iterations if convergence is not achieved.
[4] IHS transformation is considered given concerns about the LN transformation in the case that the outcome variable is zero or close to zero

Poisson regression results presented in table 2 suggest that the expansion of Medicaid resulted in about a 29 percent reduction in heroin related overdose deaths. The magnitude of the finding is evident when considering the population weighted mean number of heroin related deaths, 202 per state per year. The impact of the Medicaid expansions varies by each subcategory of opioid related overdose death. Expansion of Medicaid was associated with a 14 percent increase in methadone related deaths in the baseline model though the coefficient of interest is no longer statistically significant with the inclusion of a full set of controls.[5] The population weighted mean number of methadone related overdose deaths is about 140 per state per year. The coefficient of interest is positive and significant with respect synthetic opioid related overdose deaths in the baseline model. However, it may be the case that the rise in prevalence of illicit fentanyl has disproportionately impacted the expanding states (see section 5.3 for additional discussion). Results in table 2 suggest that the expansion of Medicaid would lead to a decrease of 58 heroin related deaths and an increase of 19 methadone related deaths in a given state, in a given year. Table 3 points to access to MAT through insurance as a crucial channel in reducing heroin deaths while also driving increases in methadone related deaths. Increases in methadone related overdose deaths may be related to increases in methadone treatment for OUD in expanding states, though methadone is also prescribed for chronic pain.

5.1 Robustness

In table 4, I reestimate equation (2) using county, year level data. Similar to the state level results, the county level results suggest that the expansion of Medicaid led to a decrease in heroin related overdose deaths and an increase in methadone related overdose deaths. Using county level data, the increase in methadone related overdose deaths is significant at the 1% level

[5] p-value = 0.188. If the control for MML is dropped, p-value = 0.106

with the inclusion of a full set of controls. Next, I test the robustness of results to different functional forms including OLS and negative binomial regression results. OLS (table 5) and negative binomial (table A7) results show that my findings are relatively robust to different distributional assumptions, though the OLS results are less precise. In table 5, again it appears that reductions in heroin deaths and increase in methadone deaths were driven by the expansion of Medicaid in states in which Medicaid benefits cover both methadone and buprenorphine.

Next, I test the robustness of these findings to alternate classifications of treatment and control. In my primary specification, states that previously expanded Medicaid and did not experience significant increases in Medicaid enrollment (D.C., MN, NJ and WA) are dropped from the sample. In table A2, I consider 3 alternate methods of coding the Medicaid expansions. In row (1), I include all 50 states plus D.C. and define Medicaid expansion dates as shown in table 8. In row (2), I include all 50 states (plus D.C.) and assign Medicaid expansion dates based on increases in Medicaid enrollment following Meinhofer and Witman (2018). Among the early expanding states that expanded Medicaid more than once, Meinhofer and Witman (2018) select the date of expansion as the expansion that led to the largest increase in enrollment. In row (3), results are shown from my primary specification (D.C., MN, NJ and WA are dropped from the sample). In row (4), Oregon and Massachusetts are dropped as both states established health care reforms and increased access to health insurance including expansion of public insurance prior to the Medicaid expansions. Results appear robust across these 4 methods of coding treatment and control.

Regression results are weighted by population. Primary results are robust when weighted by population (table 2) or unweighted (table A8). As an additional robustness check, I re-estimate the impact of the expansion of Medicaid on heroin related overdose deaths by dropping each treatment state individually (all early expanding states are included in this sample). The estimated treatment effect remains relatively stable with the exception of the specification in which California is dropped (table A6).[6]

5.2 Parallel Trends and Validity of Identification Strategy

The validity of the estimates presented rests on satisfaction of the parallel trends assumption. The parallel trends assumption is examined using visual evidence in the form of event study analysis. The event studies do not, in general, exhibit significant pre-trends. Pre-trends are of particular concern given the politicization of the ACA and the decision to expand Medicaid. I present event studies of two types. In figures 2 and 3, I utilize variation in the timing of Medicaid expansion including late expanding states and early expanding states (CA and CT only). In this specification, the event year varies among the early and late expanding states. Figure 2 reveals no visible pre-trends with respect to heroin related overdose deaths. Figure 3 reveals some visible changes in the pre-policy period with respect to methadone related deaths, though a treatment effect appears visible in the post policy period. In the second type of event study, all early and late expanding states are dropped from the sample. The treatment group includes only states that expanded Medicaid in 2014 and the control group includes all non-expanding states. In figures 4 and 5, confidence intervals are centered around or include a zero coefficient estimate in the pre-policy period. Following the expansion of Medicaid, heroin deaths appear to decrease (figure 4) and methadone deaths appear to increase (figure 5).

5.3 Illicit Fentanyl

[6] California represents the largest treatment state in my study both in terms of population and change in insurance status with over 2.5 million individuals gaining health insurance by 2017 (KFF, 2017)

In recent years, the increasing prevalence of illicit fentanyl in the U.S. has contributed to further increases in opioid mortality. Fentanyl is a synthetic opioid that is approximately 80-100 stronger than morphine (DEA, 2019). Fentanyl related overdose deaths began to dramatically increase around 2014 (see figure 1). The majority of expanding states expanded Medicaid in the same year. Unless there is a causal relationship between the expansion of Medicaid and rise in illicit fentanyl, the geographic distribution of illicit fentanyl may have differentially impacted the expansion states. From 2013-2014, the states with the largest increase in the synthetic opioid related death rate (excluding methadone) were Ohio, Massachusetts, Maryland and New Hampshire (Gladden et al., 2016). All four of these states expanded Medicaid in 2014. To the extent that there is no causal relationship between expansion of Medicaid and the distribution of illicit fentanyl, this is a confounding trend which most likely introduces downward bias in the estimated public health benefits of the expansion of Medicaid.

In table 7, I test alternate specifications to account for the rise of illicit fentanyl. In the baseline model (row 1) the expansion of Medicaid is associated with a significant increase in synthetic opioid related overdose deaths. With the inclusion of controls for other pertinent laws (row 2), the coefficient of interest is large in magnitude but no longer statistically significant. In row (3), those states that experienced the largest increase in the synthetic opioid related death rate (OH, MA, MD and NH) are dropped from the sample. After these four states are excluded, the expansion of Medicaid no longer appears to have explanatory power with respect to synthetic opioid deaths (excluding methadone). Following Meinhofer and Witman (2018), I include data from the Drug Enforcement Agency National Drug Threat Assessment (NDTA) to control for the per capita rate of seizures of illegally manufactured fentanyl. In row (4), inclusion of the control for fentanyl seizures removes the explanatory power of the Medicaid expansions with respect to synthetic opioid related overdose deaths. States in the Northeastern U.S. have been particularly hard hit by illicit fentanyl. In table A4, I consider two separate subsamples excluding states in the North East. The primary results presented in the study appear robust to the exclusion of these states. Yet in the smaller subsample, again, no relationship appears between the expansion of Medicaid and increases in fentanyl related deaths.

6. Discussion

Recent studies (Meinhofer and Witman, 2018; Maclean and Saloner, 2019; Saloner et al., 2018, Wen et al., 2017) have shown increases in prescriptions used to treat OUD and specialty treatment admissions in states that expanding Medicaid. Reductions in opioid related overdose deaths within the expanding states are most likely explained by increased access to treatment and prescriptions used to treat OUD. Maclean and Saloner (2019) do not include methadone in their study as methadone is prescribed for uses other than treatment of OUD. Results in table 6 show that the expansion of Medicaid was associated with a 20-37 percent increase in methadone prescriptions reimbursed by Medicaid, depending on the outcome variable (number of prescriptions, amount reimbursed or units reimbursed). The coefficient of interest increases in magnitude as estimated by equation (3). In other words, methadone prescriptions increased in states that expanded Medicaid in which Medicaid benefits cover methadone. These increases in methadone prescriptions in expanding states are visible in figures 6 and 7. Results in table 6 are suggestive of increased utilization of methadone therapy for OUD in expanding states relative to non-expanding states. However, methadone is commonly prescribed for chronic pain, particularly in cancer patients.

Results in tables 3 and 6 point to the public health benefits associated with increased access to MAT as well as the potential consequences associated with increasing access to methadone. Analyzing cause of death by ICD-10 codes enables the separation of methadone deaths and other synthetic opioid deaths. However, ICD-10 code T40.4 can include fentanyl, propoxyphene, meperidine, or buprenorphine (Kilby, 2015). The methodology used in this study does not allow for the separation of deaths caused by fentanyl or buprenorphine. In general, buprenorphine is considered to be a safe medication. There may be some consequences associated with increased access to buprenorphine. The Tennessee Department of Health recently found that some deaths were associated with misuse of buprenorphine and use of buprenorphine in concurrence with other prescription or illicit drugs (Tennessee Department of Health, 2018).

6.1 Measurement Error and Polysubstance Use

A major obstacle to the disaggregation approach used in this study is the prevalence of polysubstance use or the use of multiple substances by a single user. It is quite common for those struggling with OUD to use opioids of different types in concurrence or to use opioids in concurrence with other prescription drugs, other illicit drugs and/or alcohol. Polysubstance use can increase the risk of overdose. For example, use of benzodiazepines is known to increase the risk of overdose death when used with opioids (Mattson et al., 2018). In an 11-state analysis taking place from July 2016-June 2017, benzodiazepines were found present in approximately half of deaths categorized as prescription opioid–only deaths (Mattson et al., 2018). Polysubstance use is a strong predictor of misuse of prescription opioids (Morley et al., 2017)

Increased access to MAT could increase the likelihood that methadone, buprenorphine or naltrexone are present at the time of an opioid overdose. This may be more pervasive in expanding states than non-expanding states. I investigate this issue further in table A3 by re-coding methadone related deaths in a number of different ways. The county level multiple cause-of-death data contain a maximum of 20 different conditions. I collect the data and recode methadone deaths by excluding each other type of opioid related condition in the data. Across 7 methods of coding, the Medicaid expansions are still associated with a statistically significant increase in methadone related deaths. Table A3 suggests that the increase in methadone deaths in expanding states was not driven by the presence of methadone in opioid overdose cases involving other opioids.

In addition to polysubstance use, measurement error presents an obstacle in this study as misidentification of cause of death is common. ICD-10 code T50.9 classifies poisoning by unspecified drugs, medicaments and biologicals which does not identify any specific drug. From 1999-2012, 25% of drug poisoning deaths were identified with no specific drug mentioned (Rhum, 2016). Svetla et al. (2015) write: "If they [coroners and medical examiners] instead write "opioid" alone, the death will be coded to T40.6, "other and unspecified narcotics," because the information is not sufficient to assign a specific ICD-10 code (i.e., T40.2, "other opioids"; T40.3, "methadone"; or T40.4, "other synthetic narcotics"). Finally, if they write simply "drug overdose" without specifying any of the drugs involved, the contribution of the opioid analgesic will not be reflected in how the death is coded. The death will instead receive a code of "other and unspecified drugs" (T50.9)." A significant number of opioid related deaths are miscategorized in this way (Rhum, 2016). For this reason, I consider deaths classified by ICD-10 code T50.9. In table A9, whether grouping all opioids and unspecified drugs, medicaments and biologicals deaths (ICD-10 Codes T40.0-T40.4, T40.6 & T50.9) or all opioids (ICD-10 Codes T40.0-T40.4, T40.6), the estimated treatment effect is similar.

7. Conclusion

This study builds on recent research (Meinhofer and Witman, 2018; Maclean and Saloner, 2019; Saloner et al., 2018; Wen et al., 2017) which documents increases in admissions to treatment and prescriptions for medications used to treat OUD in states that expanded Medicaid. I find that the Medicaid expansions led to a decrease in heroin related overdose deaths and an increase in methadone related overdose deaths. This study contributes to our understanding of the relationship between Medicaid and the opioid epidemic but faces important limitations including measurement error. I build further on recent research by presenting evidence of increases in methadone prescriptions covered by Medicaid in expanding states. This is the most likely channel (expanded access to treatment and medications for OUD) through which the expansion of Medicaid may reduce opioid related deaths. At the same time, increasing access to MAT can increase the diversion or misuse of these medications.

An estimated 2.1 million Americans had an OUD in 2016 (SAMHSA, 2017). In 2015, an estimated 441,000 non-elderly adults were uninsured and addicted to opioids (Zur, 2017). Cost is one of many barriers to receiving treatment that individuals with OUD face, particularly those that lack health insurance. As Saloner and Barry (2018) note, targeting the supply of opioids may impact the number of newly addicted individuals but does not sufficiently alleviate the risk of overdose among the population already struggling with OUD. Evidence presented in this study could inform future demand-oriented policy to alleviate the opioid epidemic. Demand-oriented policy could include patient outreach, education about the most effective types of treatment for OUD and increasing access to treatment for OUD.

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9. Tables and Figures

Table 1: Weighted Summary Statistics

Variable	Mean	Std. Dev
State Level (1999-2016)		
All Opioids	819.74	650.80
All Opioids rate per 100k	6.76	4.43
Heroin (T40.1)	201.86	237.48
Heroin rate per 100k	1.57	1.92
Other Opioids (T40.2)	362.43	333.83
Other Opioids rate per 100k	2.89	2.21
Methadone (T40.3)	140.14	120.66
Methadone rate per 100k	1.21	0.85
Synthetic Opioids (T40.4)	136.49	233.69
Synthetic Opioids rate per 100k	1.25	2.23
Other/Unspecified Narcotics (T40.6)	112.89	121.85
Other/Unspecified Narcotics rate per 100k	0.96	1.21
Medicaid Expansion	0.13	0.33
County Level (2003-2016)		
All Opioids	74.58	115.34
All Opioids rate per 100k	7.63	7.40
Heroin (T40.1)	22.60	49.52
Heroin rate per 100k	1.81	3.08
Other Opioids (T40.2)	30.84	52.51
Other Opioids rate per 100k	3.27	3.90
Methadone (T40.3)	10.51	15.71
Methadone rate per 100k	1.40	2.15
Synthetic Opioids (T40.4)	11.60	35.12
Synthetic Opioids rate per 100k	1.48	3.32
Other/Unspecified Narcotics (T40.6)	12.20	44.51
Other/Unspecified Narcotics rate per 100k	0.93	1.97
Medicaid Expansion	0.16	0.37

Notes: Sample excludes early expanding states with previous expansions of Medicaid (DC, MN, NJ and WA)

Table 2: Impact of Medicaid Expansions on Opioid Related Deaths

	All Opioids	Heroin	Other Opioids	Methadone	Synthetic	Other Narcotics
Baseline	0.115**	-0.272**	0.0448	0.137**	0.237*	0.00559
	(0.0565)	(0.133)	(0.100)	(0.0671)	(0.131)	(0.145)
Controls for Pertinent Laws	0.0789	-0.348***	0.00457	0.0796	0.121	0.0127
	(0.0500)	(0.122)	(0.0816)	(0.0604)	(0.148)	(0.0897)
Mean of Dependent	819.74	201.86	362.43	140.14	136.49	112.89
N	846	846	846	846	846	846

Notes: State year level data: 1999-2016. Population weighted Poisson regression estimates. Models include year fixed effect and state fixed effect. Expanding states with previous expansion have been dropped from the sample (DC, MN, NJ and WA). Controls include the natural log of the state population, age and demographic controls and the unemployment rate. Standard errors in parentheses are clustered at the state level. * p<0.10, ** p<0.05, *** p<0.01

Table 3: Medicaid Expansion Interaction Model

	All Opioids	Heroin	Other Opioids	Methadone	Synthetic	Other Narcotics
Medicaid Expansion*MAT	0.140**	-0.362***	0.0478	0.139**	0.264**	0.189
	(0.0674)	(0.125)	(0.105)	(0.0680)	(0.129)	(0.130)
Other Expanding States	-0.0384	0.256*	0.0349	0.140	0.141	-0.966***
	(0.0758)	(0.141)	(0.167)	(0.145)	(0.241)	(0.278)
Mean of Dependent	819.74	201.86	362.43	140.14	136.49	112.89
N	846	846	846	846	846	846

Notes: State year level data: 1999-2016. Population weighted Poisson regression estimates. Models include year fixed effect and state fixed effect. Expanding states with previous expansion have been dropped from the sample (DC, MN, NJ and WA). Controls include the natural log of the state population, age and demographic controls and the unemployment rate. Standard errors in parentheses are clustered at the state level. * p<0.10, ** p<0.05, *** p<0.01

Table 4: Robustness to County Level Data

	All Opioids	Heroin	Other Opioids	Methadone	Synthetic	Other Narcotics
Baseline	0.0794	-0.0506	0.0753	0.406***	0.426	-0.298
	(0.0823)	(0.239)	(0.121)	(0.0906)	(0.299)	(0.246)
Controls for Pertinent Laws	0.0182	-0.250*	0.00518	0.309***	0.224	-0.119
	(0.0671)	(0.128)	(0.0717)	(0.0862)	(0.227)	(0.109)
Mean of Dependent	74.58	22.60	30.84	10.51	11.60	12.20
N	41,853	41,853	41,853	41,853	41,853	41,853

Notes: County year level data: 2003-2016. Population weighted Poisson regression estimates. Models include year fixed effect and state fixed effect. Expanding states with previous expansion have been dropped from the sample (DC, MN, NJ and WA). Controls include the natural log of the county population, age and demographic controls and the unemployment rate. Standard errors in parentheses are clustered at the state level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 5: Robustness to Functional Form - OLS

	All Opioids	Heroin	Other Opioids	Methadone	Synthetic	Other Narcotics
Inverse Hyperbolic Sine (Death Rate)						
Medicaid Expansion	0.0785	-0.139	-0.0165	0.103*	0.117	0.0532
	(0.0724)	(0.101)	(0.0834)	(0.0540)	(0.120)	(0.0685)
Natural Log (Death Rate + 1)						
Medicaid Expansion	0.0841	-0.0798	-0.0112	0.0770*	0.109	0.0351
	(0.0732)	(0.0793)	(0.0646)	(0.0396)	(0.0966)	(0.0509)
Interaction Model						
Inverse Hyperbolic Sine (Death Rate)						
Medicaid Expansion*MAT	0.104	-0.253**	-0.0275	0.140**	0.189	0.134**
	(0.0828)	(0.111)	(0.0916)	(0.0554)	(0.134)	(0.0628)
Other Expanding States	-0.0234	0.115	0.0113	0.0166	-0.0647	-0.223
	(0.0944)	(0.129)	(0.105)	(0.0804)	(0.177)	(0.181)
Natural Log (Death Rate + 1)						
Medicaid Expansion*MAT	0.109	-0.163*	-0.0156	0.105**	0.166	0.0980**
	(0.0821)	(0.0887)	(0.0710)	(0.0406)	(0.110)	(0.0471)
Other Expanding States	-0.0204	0.106	0.00285	0.0121	-0.0370	-0.175
	(0.0986)	(0.102)	(0.0809)	(0.0593)	(0.139)	(0.137)
Mean of Dependent Before Transformation	6.76	1.57	2.89	1.21	1.25	0.96
N	846	846	846	846	846	846

Notes: State year level data: 1999-2016. Population weighted OLS estimates. Models include year fixed effect and state fixed effect. Expanding states with previous expansion have been dropped from the sample (DC, MN, NJ and WA). Controls include pertinent laws (NALs, GSLs, PDMPs, "must access" PDMPs, MMLs and PCLs), age and demographic controls and the unemployment rate. Standard errors in parentheses are clustered at the state level. * p<0.10, ** p<0.05, *** p<0.01

Table 6: Methadone Prescriptions - Medicaid State Drug Utilization Data

	Log Number of Prescriptions	Log Medicaid Amount Reimbursed	Log Units Reimbursed
Baseline			
Medicaid Expansion	0.299**	0.179	0.205*
	(0.116)	(0.159)	(0.116)
Interaction			
Medicaid Expansion*MAT	0.367**	0.204	0.240*
	(0.140)	(0.184)	(0.133)
Other Expanding States	0.0772	0.0963	0.113
	(0.206)	(0.220)	(0.171)
Mean of Dependent Before Transformation	5,183.41	107,727.00	569,722.10
N	2,009	1,857	1,475

Notes: Medicaid State Drug Utilization data 2006-2016, state, quarterly level. Population weighted OLS estimates. Models includes year fixed effect, state fixed effect and control for the natural log of the state population. Quarterly state population estimates from the Bureau of Economic Analysis Personal Income Summary 2010-2016. Annual population data used as a proxy (2006-2009) from NCHS Bridged Race Population Estimates. Standard errors in parentheses are clustered at the state level. * p<0.10, ** p<0.05, *** p<0.01

Table 7: Alternate Specifications, Dependent variable: T40.4 Other Synthetic Narcotics

	Poisson	OLS - Inverse Hyperbolic Sine	OLS - Natural Log (Death Rate + 1)
(1) Baseline	0.230*	0.220*	0.187*
	(0.128)	(0.122)	(0.0994)
N	918	918	918
(2) Controls for Pertinent Laws	0.107	0.104	0.0979
	(0.149)	(0.130)	(0.104)
N	918	918	918
(3) Drop NH, MA, OH, MD	-0.0502	-0.00220	0.00580
	(0.152)	(0.120)	(0.0929)
N	846	846	846
(4) Full Sample with Control	0.00789	-0.0150	-0.00604
for Fentanyl Seizures per Capita	(0.146)	(0.103)	(0.0792)
N	918	918	918
Mean of Dependent Before Transformation	136.49	1.25	1.25

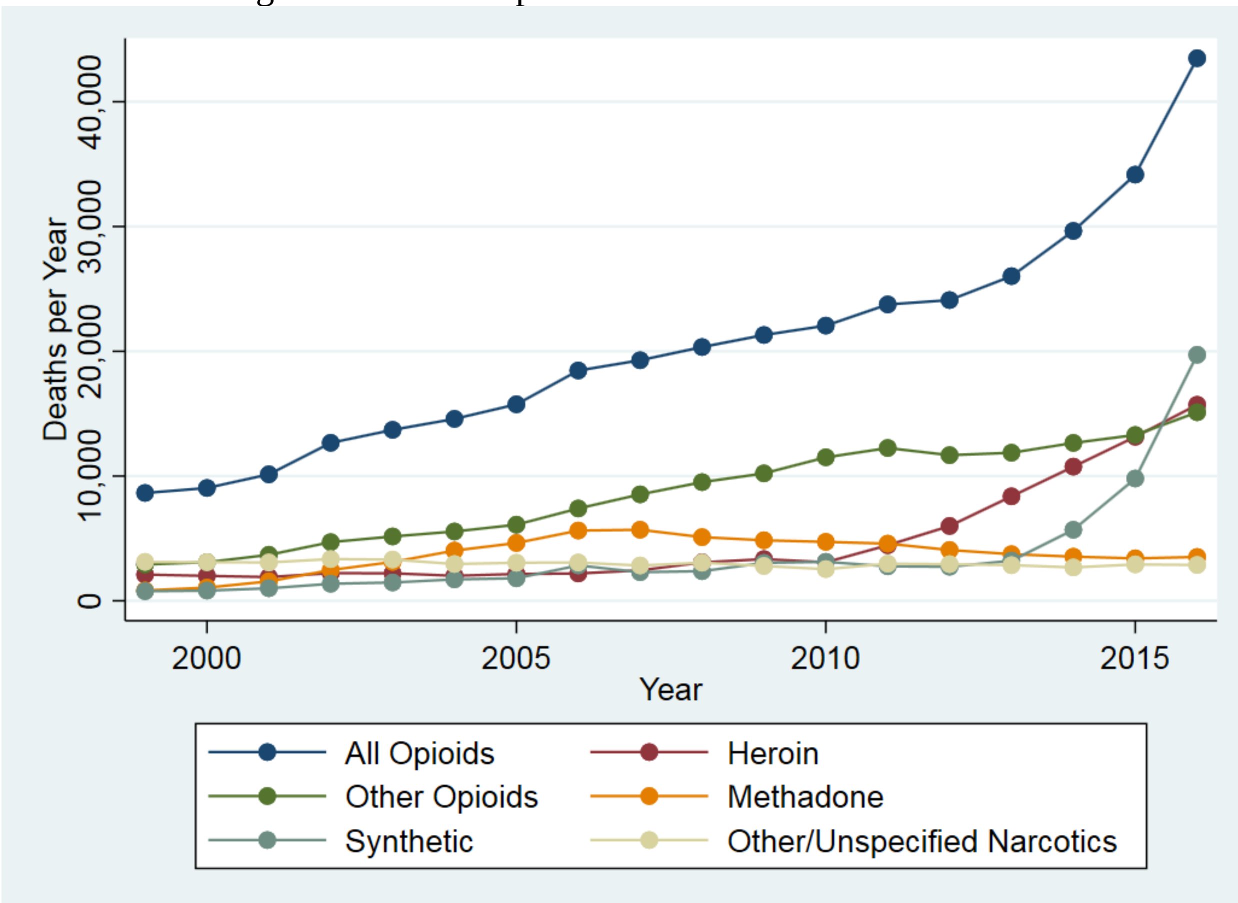
Notes: State year level data: 1999-2016. Population weighted regression estimates. Models include year fixed effect and state fixed effect. Controls include age and demographic controls and the unemployment rate. Standard errors in parentheses are clustered at the state level. * p<0.10, ** p<0.05, *** p<0.01

Table 8: ACA Medicaid Expansions from 2010-2016

State	Expansion Date
California	7/1/2011
Connecticut	4/1/2010
District of Columbia	7/1/2010
Minnesota	3/1/2011
New Jersey	4/14/2011
Washington	1/3/2011
Arizona	1/1/2014
Arkansas	1/1/2014
Colorado	1/1/2014
Delaware	1/1/2014
Hawaii	1/1/2014
Illinois	1/1/2014
Iowa	1/1/2014
Kentucky	1/1/2014
Maryland	1/1/2014
Massachusetts	1/1/2014
Michigan	4/1/2014
Nevada	1/1/2014
New Hampshire	8/15/2014
New Mexico	1/1/2014
New York	1/1/2014
North Dakota	1/1/2014
Ohio	1/1/2014
Oregon	1/1/2014
Rhode Island	1/1/2014
Vermont	1/1/2014
West Virginia	1/1/2014
Alaska	9/1/2015
Indiana	2/1/2015
Montana	1/1/2016
Louisiana	7/1/2016
Pennsylvania	1/1/2015

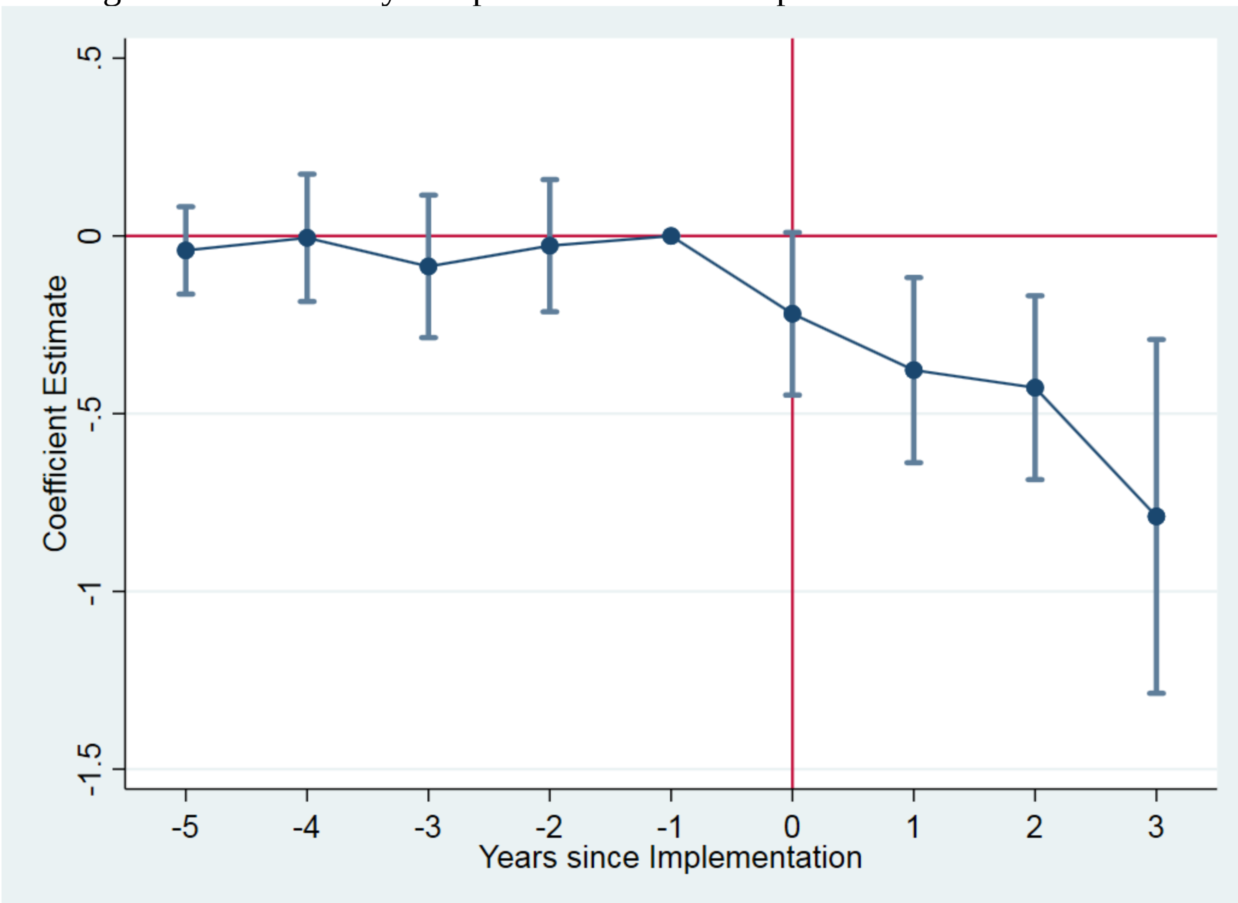
Source: Maclean and Saloner (2019)

Figure 1: Annual Opioid Overdose Deaths in the U.S.



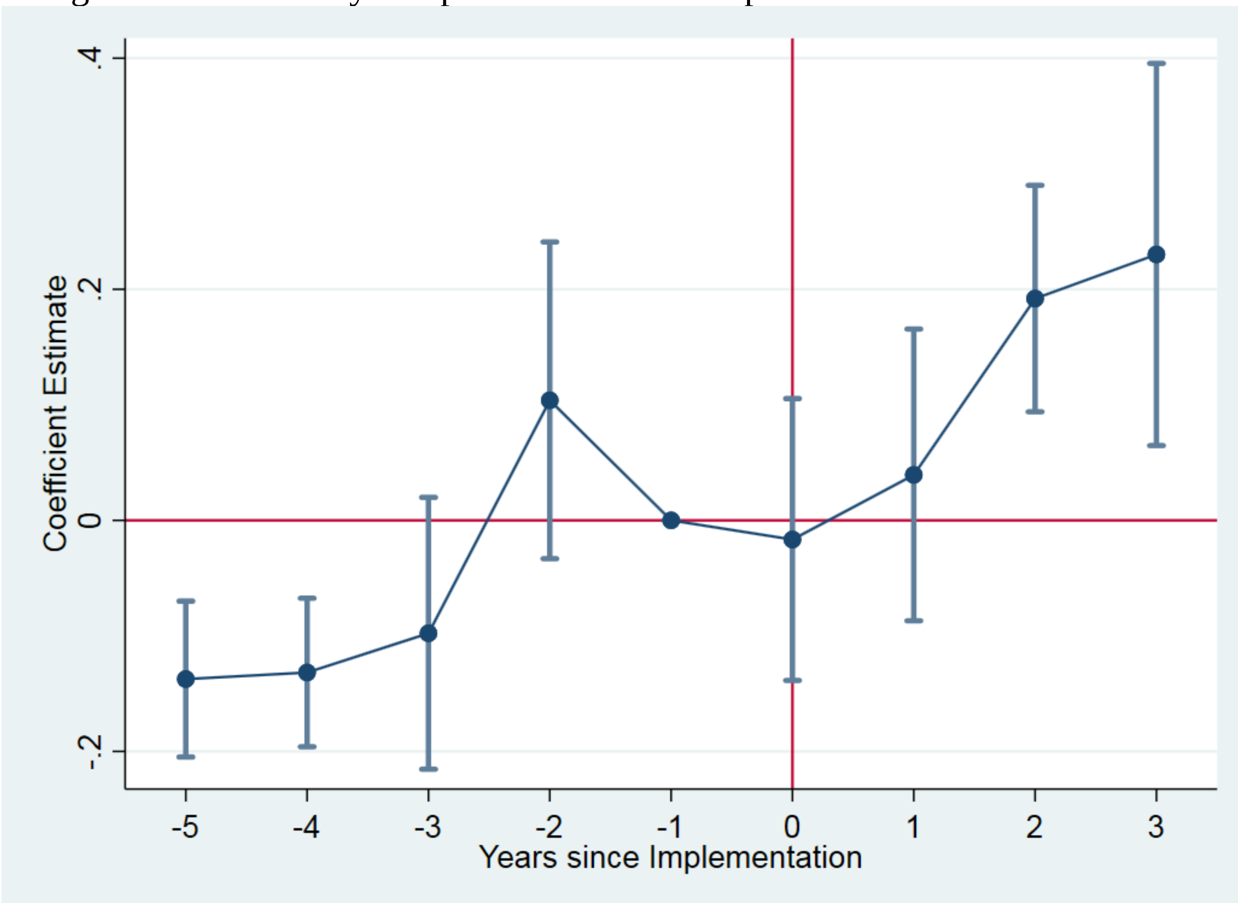
Notes: Data obtained from CDC WONDER Online Database, Multiple Cause of Death 1999-2016. Deaths identified by *International Classification of Disease, Tenth Revision* (ICD-10) codes as follows: T40.0-T40.4, T40.6 (all opioids), T40.1 (heroin), T40.2 (other opioids), T40.3 (methadone), T40.4 (other synthetic narcotics) and T40.6 (other/unspecified narcotics)

Figure 2: Event Study - Impact of Medicaid Expansions on Heroin Deaths



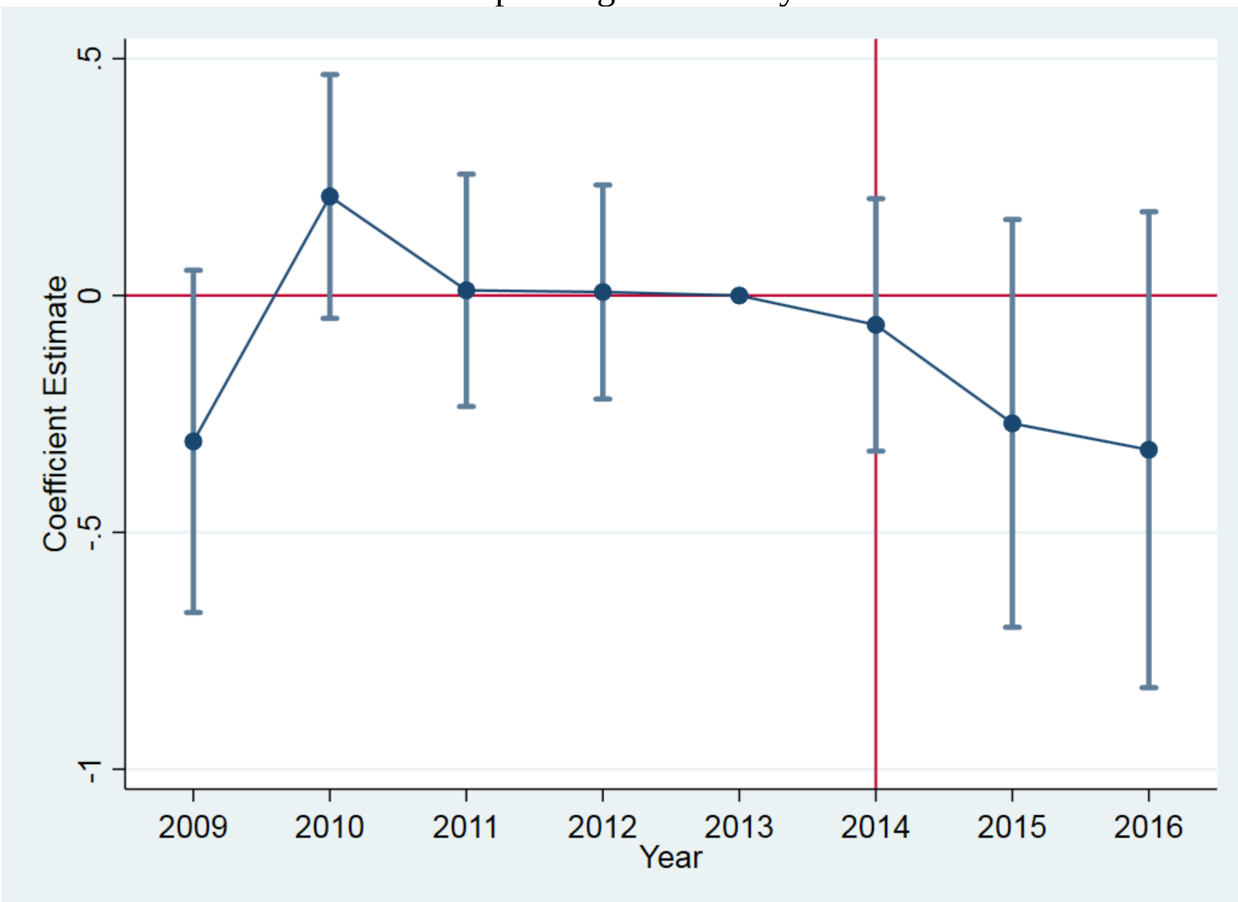
Notes: State year level data: 1999-2016. Population weighted Poisson regression estimates. Model includes year fixed effect and state fixed effect. Expanding states with previous expansion have been dropped from the sample (DC, MN, NJ and WA). Controls include the natural log of the state population, age and demographic controls, the unemployment rate and other pertinent laws (NALs, GSLs, PDMPs, "must access" PDMPs, MMLs and PCLs). Standard errors are adjusted for clustering at the state level.

Figure 3: Event Study - Impact of Medicaid Expansions on Methadone Deaths



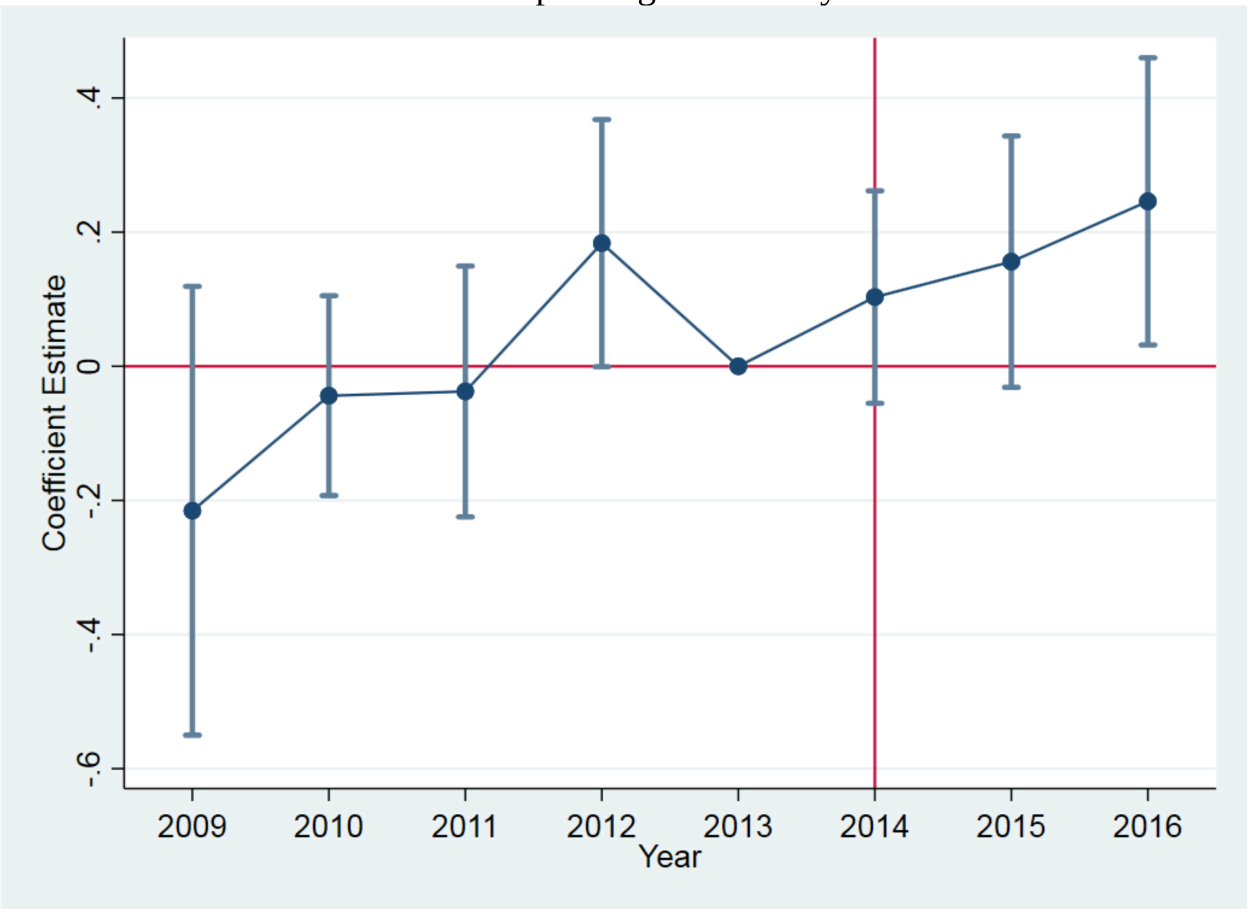
Notes: State year level data: 1999-2016. Population weighted Poisson regression estimates. Model includes year fixed effect and state fixed effect. Expanding states with previous expansion have been dropped from the sample (DC, MN, NJ and WA). Controls include the natural log of the state population, age and demographic controls, the unemployment rate and other pertinent laws (NALs, GSLs, PDMPs, "must access" PDMPs, MMLs and PCLs). Standard errors are adjusted for clustering at the state level.

Figure 4: Event Study - Impact of Medicaid Expansions on Heroin Deaths: 2014 Expanding States Only



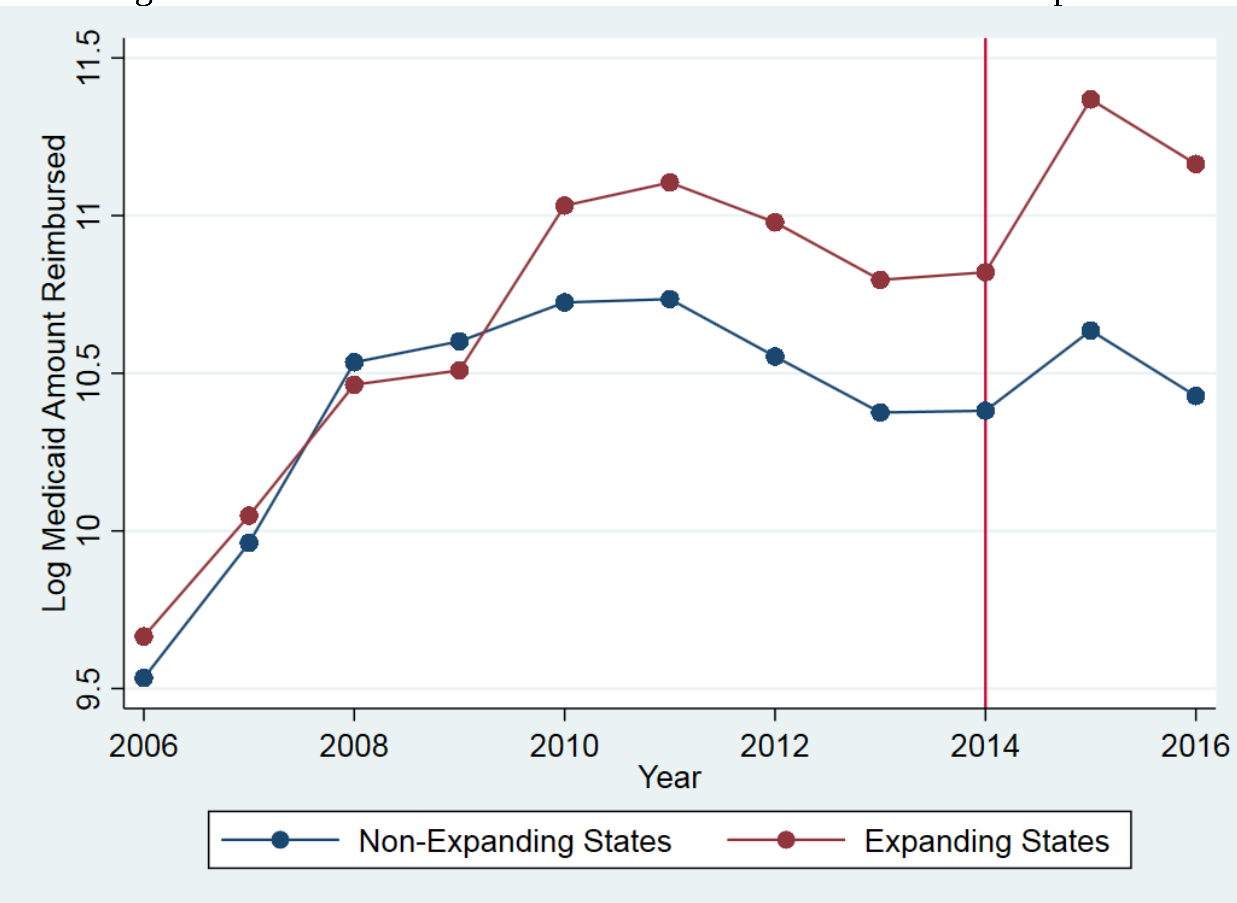
Notes: State year level data: 1999-2016. Population weighted Poisson regression estimates. Model includes year fixed effect and state fixed effect. All early and late expanding states dropped (treatment group includes only states that expanded Medicaid on Jan 1st 2014). Controls include the natural log of the state population, age and demographic controls, the unemployment rate and other pertinent laws (NALs, GSLs, PDMPs, "must access" PDMPs, MMLs and PCLs). Standard errors are adjusted for clustering at the state level.

Figure 5: Event Study - Impact of Medicaid Expansions on Methadone Deaths: 2014 Expanding States Only



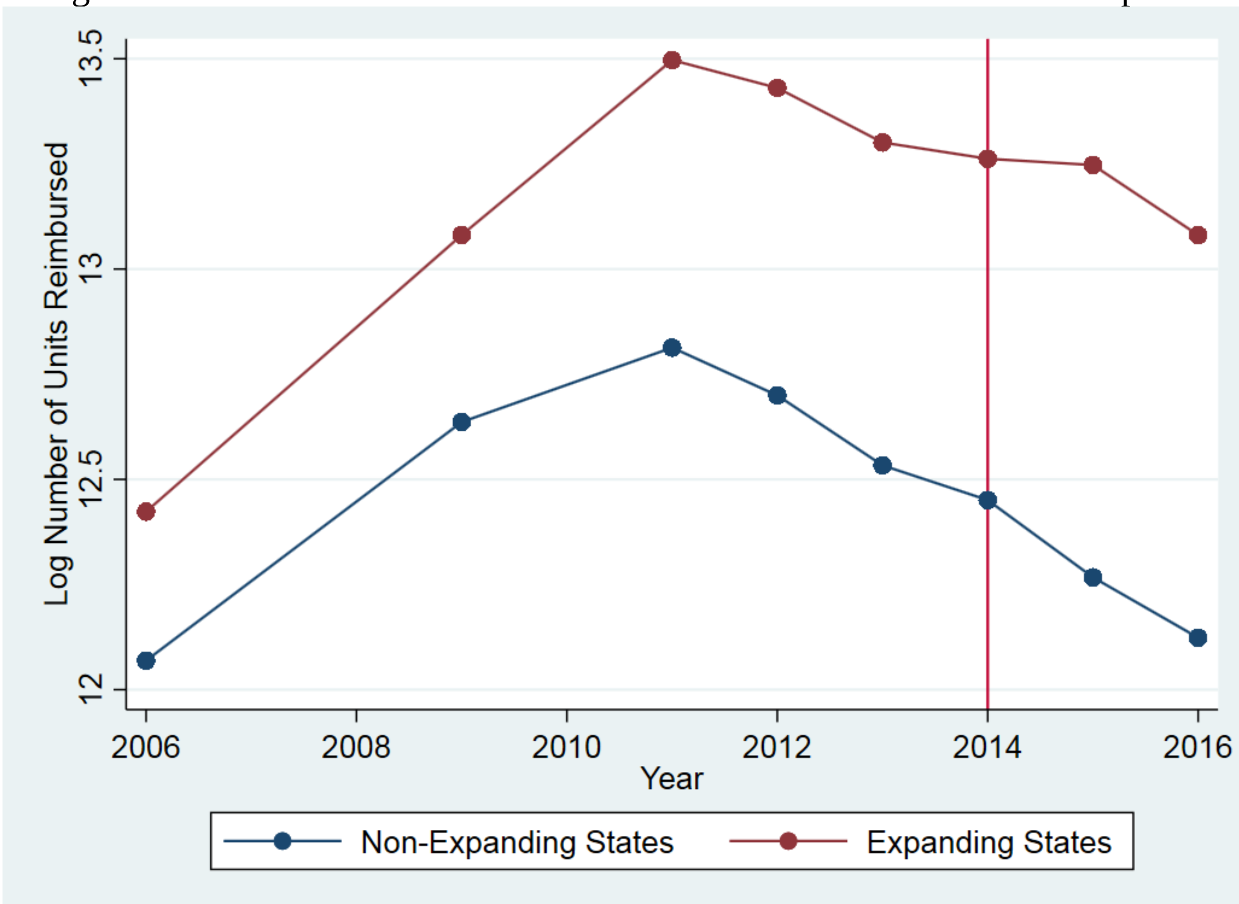
Notes: State year level data: 1999-2016. Population weighted Poisson regression estimates. Model includes year fixed effect and state fixed effect. All early and late expanding states dropped (treatment group includes only states that expanded Medicaid on Jan 1st 2014). Controls include the natural log of the state population, age and demographic controls, the unemployment rate and other pertinent laws (NALs, GSLs, PDMPs, "must access" PDMPs, MMLs and PCLs). Standard errors are adjusted for clustering at the state level.

Figure 6: Medicaid Amount Reimbursed for Methadone Prescriptions



Notes: Medicaid State Drug Utilization data: 2006-2016. All early and late expanding states dropped (treatment group includes only states that expanded Medicaid on Jan 1st 2014).

Figure 7: Medicaid Number of Units Reimbursed for Methadone Prescriptions



Notes: Medicaid State Drug Utilization data: 2006-2016. All early and late expanding states dropped (treatment group includes only states that expanded Medicaid on Jan 1st 2014).

10. Appendix

Table A1: State Law Effective Dates

State	PDMP Date of Implementation	"Must Access" PDMP	Naloxone Access Laws	Good Samaritan Laws	Pain Clinic Laws	Medical Marijuana Laws
Alabama	Apr-2007		Jun-2015	Jun-2015	2013	
Alaska	Jan-2012		Mar-2016	Oct-2014		
Arizona	Dec-2008					Apr-2011
Arkansas	Mar-2013		Jul-2015	Jul-2015		
California	Jan-2009		Jan-2008	Jan-2013		
Colorado	Feb-2008		May-2013	May-2012		
Connecticut	Jul-2008		Oct-2003	Oct-2011		Oct-2012
D.C.			Mar-2013	Mar-2013		Jul-2010
Delaware	Aug-2012	2012	Aug-2014	Aug-2013		Jul-2011
Florida	Oct-2011		Jun-2015	Oct-2012	2010	
Georgia	Jul-2013		Apr-2014	Apr-2014	2013	
Hawaii	1996		Jun-2016	Jul-2015		
Idaho	1998		Jul-2015			
Illinois	1999		Jan-2010	Jun-2012		Jan-2014
Indiana	Jan-2007		Apr-2015			
Iowa	Mar-2009		May-2016			
Kansas	Apr-2011					
Kentucky	1999	2012	Jun-2013	Mar-2015	2012	
Louisiana	Jan-2009	2008*	Aug-2015	Aug-2014	2005	
Maine	Jan-2005		Apr-2014			
Maryland	Jan-2014		Oct-2013	Oct-2014		Jun-2014
Massachusetts	Aug-2010		Aug-2012	Aug-2012		Jan-2013
Michigan	1998		Oct-2014			Dec-2008
Minnesota	Apr-2010		May-2014	Jul-2014		May-2014
Mississippi	Dec-2005		Jul-2015	Jul-2015	2012	
Missouri						
Montana	Oct-2012					
Nebraska			May-2015			
Nevada	1997	2007	Oct-2015	Oct-2015		
New Hampshire			Jun-2015	Sep-2015		Jul-2013
New Jersey	Jan-2012		Jul-2013	May-2013		Oct-2010
New Mexico	Aug-2012	2012	Apr-2001	Jun-2007		Jul-2007
New York	1973	2013	Jun-2014	Sep-2011		Jul-2014
North Carolina	Oct-2007		Apr-2013	Apr-2013		
North Dakota	Jan-2007		Aug-2015	Aug-2015		

Ohio	Oct-2011	2012	Mar-2014		2011	
Oklahoma	Jul-2006	2011	Nov-2013			
Oregon	Sep-2011		Jun-2013	Jan-2016		
Pennsylvania			Nov-2014	Dec-2014		
Rhode Island	2001		Jun-2012	Jun-2012		Jan-2006
South Carolina	Jun-2008		Jun-2015			
South Dakota	Mar-2012		Jul-2016			
Tennessee	1990	2013	Jul-2014	Jul-2015	2012	
Texas	1989		Sep-2015		2009	
Utah	1997		May-2014	Mar-2014		
Vermont	Apr-2009		Jul-2013	Jun-2013		Jul-2004
Virginia	Jun-2006		Jul-2013	Jul-2015		
Washington	Jan-2012		Jun-2010	Jun-2010		
West Virginia	1995	2012	May-2015	Jun-2015	2012	
Wisconsin	May-2013		Apr-2014	Apr-2014		
Wyoming	Jan-2004					

Sources: The National Alliance For Model State Drug Laws (2018), Kilby (2015), Buchmueller and Carey (2018), Rees et al. (2017), Meinhofer and Witman (2018), Baggio et al. (2018). Notes: This measure of PDMP includes earlier substances monitoring programs. Louisiana started receiving prescription data in 2008 and allowed users to access PDMP data on Jan 1st 2009.

Table A2: Robustness to Definition of Treatment and Control

	All Opioids	Heroin	Other Opioids	Methadone	Synthetic	Other Narcotics
(1) Full Sample	0.0682	-0.308***	0.00212	0.0483	0.107	0.0523
	(0.0545)	(0.107)	(0.0809)	(0.0620)	(0.149)	(0.0889)
N	918	918	918	918	918	918
(2) Coding following Meinhofer	0.1000*	-0.347**	0.0520	0.146***	-0.00913	0.224*
and Witman (2018)	(0.0569)	(0.168)	(0.129)	(0.0554)	(0.192)	(0.118)
N	918	918	918	918	918	918
(3) Preferred Specification	0.0789	-0.348***	0.00457	0.0796	0.121	0.0127
	(0.0500)	(0.122)	(0.0816)	(0.0604)	(0.148)	(0.0897)
N	864	864	864	864	864	864
(4) Preferred Specification	0.0751	-0.320***	0.00256	0.0816	0.0983	0.0587
and Drop MA and OR	(0.0505)	(0.121)	(0.0838)	(0.0631)	(0.151)	(0.0943)
N	810	810	810	810	810	810

Notes: State year level data: 1999-2016. Population weighted Poisson Regression estimates. Models include year fixed effect and state fixed effect. Controls include pertinent laws (NALs, GSLs, PDMPs, "must access" PDMPs, MMLs and PCLs), age and demographic controls and the unemployment rate. Standard errors in parentheses are clustered at the state level. * p<0.10, ** p<0.05, *** p<0.01

Table A3: Methadone Coding Sensitivity Analysis

Dependent Variable	Poisson	OLS - Inverse Hyperbolic Sine	OLS - Natural Log (Death Rate + 1)	Number of Deaths
(1) Methadone (T40.3) is listed as condition 1-4	0.309***	0.137**	0.106**	60,793
	(0.0862)	(0.0600)	(0.0465)	
(2) Methadone (T40.3) is listed as condition 1	0.274***	0.122**	0.0941**	39,676
	(0.0901)	(0.0573)	(0.0441)	
(3) Methadone (T40.3) is listed as condition 1 excluding	0.270***	0.120**	0.0927**	38,829
Other Synthetic Narcotics (T40.4) is listed as condition 2-9	(0.0898)	(0.0568)	(0.0438)	
(4) Methadone (T40.3) is listed as condition 1 excluding	0.257***	0.119**	0.0914**	34,997
Other Opioids (T40.2) is listed as condition 2-9	(0.0894)	(0.0579)	(0.0445)	
(5) Methadone (T40.3) is listed as condition 1 excluding	0.272***	0.122**	0.0937**	39,438
Heroin (T40.1) is listed as condition 2-9	(0.0901)	(0.0572)	(0.0441)	
(6) Methadone (T40.3) is listed as condition 1 excluding	0.269***	0.122**	0.0940**	39,154
Other/Unspecified Narcotics (T40.6) is listed as condition 2-9	(0.0914)	(0.0570)	(0.0439)	
(7) Methadone (T40.3) is listed as condition 1, excluding	0.241***	0.116**	0.0892**	33,749
any other opioid (ICD-10 code T40.1, T40.2, T40.4, T40.6)	(0.0902)	(0.0568)	(0.0436)	
is listed as condition 2-6				
N	41,853	41,853	41,853	

Notes: County year level data: 2003-2016. Models presented in rows use various methods for coding of cause of death. Population weighted regression estimates. Models include year fixed effect and state fixed effect. Expanding states with previous expansion have been dropped from the sample (DC, MN, NJ and WA). Controls include pertinent laws (NALs, GSLs, PDMPs, "must access" PDMPs, MMLs and PCLs), age and demographic controls and the unemployment rate. Standard errors in parentheses are clustered at the state level. * p<0.10, ** p<0.05, *** p<0.01

Table A4: Drop Northeast

	All Opioids	Heroin	Other Opioids	Methadone	Synthetic	Other Narcotics
Drop New England	0.000875	-0.267*	0.0000281	0.230**	0.196	0.0153
	(0.0672)	(0.140)	(0.0732)	(0.0991)	(0.236)	(0.0844)
N	42,987	42,987	42,987	42,987	42,987	42,987
Drop New England,	-0.0517	-0.314*	-0.00548	0.297***	-0.0122	-0.0225
NY, PA, OH and MD	(0.0673)	(0.171)	(0.0708)	(0.105)	(0.214)	(0.0782)
N	39,613	39,613	39,613	39,613	39,613	39,613

Notes: County year level data: 2003-2016. Population weighted Poisson regression estimates. Models include year fixed effect and state fixed effect. Controls include pertinent laws (NALs, GSLs, PDMPs, "must access" PDMPs, MMLs and PCLs), age and demographic controls and the unemployment rate. Standard errors in parentheses are clustered at the state level. * p<0.10, ** p<0.05, *** p<0.01

Table A5: State and County Level Results Using the Same Sample Years

	All Opioids	Heroin	Other Opioids	Methadone	Synthetic	Other Narcotics
State Level Data						
Baseline	0.0612	-0.244**	0.00214	0.0211	0.296**	0.0233
	(0.0483)	(0.120)	(0.0785)	(0.0462)	(0.130)	(0.137)
Controls for Pertinent Laws	0.0315	-0.300***	-0.0236	-0.0168	0.179	0.0376
	(0.0449)	(0.113)	(0.0689)	(0.0536)	(0.144)	(0.0776)
Control for Fentanyl Seizures	-0.0117	-0.296**	-0.0265	-0.0211	0.0944	-0.0345
	(0.0451)	(0.118)	(0.0701)	(0.0585)	(0.140)	(0.0697)
Mean of Dependent	920.28	228.65	410.35	163.13	162.03	108.67
N	658	658	658	658	658	658
County Level Data						
Baseline	0.0794	-0.0506	0.0753	0.406***	0.426	-0.298
	(0.0823)	(0.239)	(0.121)	(0.0906)	(0.299)	(0.246)
Controls for Pertinent Laws	0.0182	-0.250*	0.00518	0.309***	0.224	-0.119
	(0.0671)	(0.128)	(0.0717)	(0.0862)	(0.227)	(0.109)
Control for Fentanyl Seizures	0.0162	-0.253**	0.00360	0.315***	0.227	-0.122
	(0.0665)	(0.129)	(0.0720)	(0.0867)	(0.226)	(0.109)
Mean of Dependent	74.58	22.60	30.84	10.51	11.60	12.20
N	41,853	41,853	41,853	41,853	41,853	41,853

Notes: Data: 2003-2016. Population weighted Poisson regression estimates. Models include year fixed effect and state fixed effect. Expanding states with previous expansion have been dropped from the sample (DC, MN, NJ and WA). Controls include the natural log of the state population, age and demographic controls and the unemployment rate. Standard errors in parentheses are clustered at the state level. * p<0.10, ** p<0.05, *** p<0.01

Table A6: Impact of Medicaid Expansions on Heroin Deaths - Drop Each Individual Treatment State

		Early Expanding States						2014 Expanding States			
State Dropped	50 States + D.C.	CA	CT	D.C.	MN	NJ	WA	AZ	AR	CO	DE
	-0.302***	-0.196	-0.296***	-0.303***	-0.302***	-0.329***	-0.307***	-0.331***	-0.302***	-0.307***	-0.302***
	(0.106)	(0.134)	(0.107)	(0.107)	(0.107)	(0.116)	(0.107)	(0.107)	(0.106)	(0.107)	(0.106)
N	918	900	900	900	900	900	900	900	900	900	900
	2014 Expanding States										
State Dropped	HI	IL	IA	KY	MD	MA	MI	NV	NH	NM	NY
	-0.301***	-0.321***	-0.303***	-0.303***	-0.302***	-0.293***	-0.361***	-0.302***	-0.301***	-0.303***	-0.197**
	(0.106)	(0.109)	(0.106)	(0.107)	(0.108)	(0.108)	(0.0910)	(0.106)	(0.106)	(0.106)	(0.0886)
N	900	900	900	900	900	900	900	900	900	900	900
	2014 Expanding States						Late Expanding States				
State Dropped	ND	OH	OR	RI	VT	WV	AK	IN	MT	LA	PA
	-0.302***	-0.295**	-0.295***	-0.301***	-0.302***	-0.300***	-0.302***	-0.312***	-0.302***	-0.303***	-0.261**
	(0.106)	(0.120)	(0.105)	(0.106)	(0.106)	(0.106)	(0.106)	(0.105)	(0.106)	(0.107)	(0.114)
N	900	900	900	900	900	900	900	900	900	900	900

Notes: Dependent variable: Heroin deaths. State year level data: 1999-2016. Population weighted Poisson regression estimates. Models include year fixed effect and state fixed effect. Controls include pertinent laws (NALs, GSLs, PDMPs, "must access" PDMPs, MMLs and PCLs), age and demographic controls and the unemployment rate. Standard errors in parentheses are clustered at the state level. * p<0.10, ** p<0.05, *** p<0.01

Table A7: Robustness to Functional Form - Negative Binomial

	All Opioids	Heroin	Other Opioids	Methadone	Synthetic	Other Narcotics
Baseline	0.0883	-0.346**	-0.0495	0.192**	0.113	0.0241
	(0.0560)	(0.163)	(0.129)	(0.0746)	(0.114)	(0.124)
Controls for Pertinent Laws	0.0616	-0.399***	-0.0853	0.156***	0.0263	0.0158
	(0.0561)	(0.143)	(0.113)	(0.0549)	(0.128)	(0.105)
Controls for Fentanyl Seizures	0.0226	-0.402***	-0.0835	0.161***	-0.0694	-0.0233
	(0.0527)	(0.148)	(0.114)	(0.0571)	(0.122)	(0.103)
Mean of Dependent	819.74	201.86	362.43	140.14	136.49	112.89
N	846	846	846	846	846	846

Notes: State year level data: 1999-2016. Population weighted Negative Binomial regression estimates. Models include year fixed effect and state fixed effect. Expanding states with previous expansion have been dropped from the sample (DC, MN, NJ and WA). Controls include the natural log of the state population, age and demographic controls and the unemployment rate. Standard errors in parentheses are clustered at the state level. * p<0.10, ** p<0.05, *** p<0.01

Table A8: Robustness to Estimation of Unweighted Poisson

	All Opioids	Heroin	Other Opioids	Methadone	Synthetic	Other Narcotics
Baseline	0.0828	-0.217*	-0.0397	0.129*	0.220	0.0309
	(0.0656)	(0.132)	(0.0786)	(0.0664)	(0.160)	(0.157)
Controls for Pertinent Laws	0.0433	-0.306***	-0.0720	0.100*	0.0879	0.0110
	(0.0680)	(0.111)	(0.0795)	(0.0570)	(0.165)	(0.103)
Controls for Fentanyl Seizures	-0.00609	-0.308***	-0.0797	0.105*	-0.0142	-0.0545
	(0.0612)	(0.117)	(0.0815)	(0.0587)	(0.150)	(0.106)
Mean of Dependent	819.74	201.86	362.43	140.14	136.49	112.89
N	846	846	846	846	846	846

Notes: State year level data: 1999-2016. Poisson regression estimates. Models include year fixed effect and state fixed effect. Expanding states with previous expansion have been dropped from the sample (DC, MN, NJ and WA). Controls include the natural log of the state population, age and demographic controls and the unemployment rate. Standard errors in parentheses are clustered at the state level. * p<0.10, ** p<0.05, *** p<0.01

Table A9: Inclusion of ICD-10 Code: T50.9

	All Opioids	All Opioids & T50.9
Poisson		
Medicaid Expansion	0.0778	0.0546
	(0.0489)	(0.0360)
OLS - Inverse Hyperbolic Sine (Death Rate)	0.0939	0.0719
Medicaid Expansion	(0.0838)	(0.0656)
Natural Log (Death Rate + 1)	0.101	0.0721
Medicaid Expansion	(0.0852)	(0.0661)
N	846	846

Notes: State year level data: 1999-2016. Population weighted regression estimates. Models include year fixed effect and state fixed effect. Controls include pertinent laws (NALs, GSLs, PDMPs, "must access" PDMPs, MMLs and PCLs), age and demographic controls and the unemployment rate. Standard errors in parentheses are clustered at the state level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$