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

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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. I utilize variation in states' decisions to expand Medicaid, in the timing of expansion and in the pre-policy uninsured rate at the state and county level. Opioid related mortality data are examined from 1999-2016 using the multiple cause of death files obtained from the Centers for Disease Control and Prevention. My findings suggest the implementation of Medicaid expansion resulted in about a 30% reduction in heroin deaths, a 26% reduction in other unspecified narcotics deaths and a 14.5% increase in methadone related deaths. My study builds on recent work that shows increases in prescriptions to treat opioid use disorder in expanding states relative to non-expanding states.

1. Introduction

The rise in opioid use and opioid related overdose deaths has been the most significant substance abuse trend in the United States in recent years. 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, including public insurance expansion, 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 abuse of opioids. In this study, I examine two channels through which expansion of health insurance may impact the opioid epidemic: increased access to SUD treatment and increased access to 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. This study identifies the causal impact of health insurance expansion resulting from the ACA on overdose deaths by using variation in Medicaid expansions and private market expansion of health insurance across states and over time. This is the first study to document the decreases (heroin and other/unspecified narcotics) and increases (methadone) in opioid related deaths in expanding states relative to non-expanding states. The decline in heroin deaths is robust to a number of different specifications and appears validated by event study analysis. Understanding these effects is of particular importance given recent legislative proposals to alter or repeal the ACA and the massive numbers of opioid users dying each year.

2. Policy Background

Public insurance is playing an important role in the American opioid epidemic. More specifically, Medicaid is the largest source of funding for behavioral health treatment in the United States (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 increases in social and occupational outcomes (National Institute on Drug Abuse, 2012). The American Society of Addiction Medicine (ASAM) guidelines for treatment of opioid use disorder recommend that psychosocial treatment be used in concurrence with opioid use disorder medications (Grogan et al. 2016). Such treatments (both impatient and outpatient) and medications can be prohibitively costly for the uninsured.

One of the primary goals of the ACA was to increase access to health care for the large number of uninsured in the US. Toward this goal, the ACA increased the minimum income requirement for Medicaid coverage to 138% of the poverty level. As a result of a 2012 Supreme Court decision, the decision to expanded Medicaid was left to states. 31 states and Washington D.C. have implemented the expansion of Medicaid to date (KFF, 2018).[1] For states that opted into Medicaid expansion, increasing the minimum income requirement has created a large new pool of individuals eligible for Medicaid coverage. Prior to the full implementation of the ACA, the uninsured rate among the non-elderly population had climbed to 18.2% in 2010 (KFF, 2017). The uninsured rate among the non-elderly declined to 10.5% by 2015 (KFF, 2017). Medicaid enrollment has increased by 17 million (KFF, 2017). Medicaid is funded by state governments as well as the federal government. In order to alleviate the cost at the state level of adding

[1] Maine voted to expand Medicaid in November 2017, though expansion has not yet been enacted. The Virginia General Assembly approved Medicaid Expansion in May of 2018.

individuals to Medicaid, funding for the newly eligible would be provided by the federal government for the first three years starting in 2014 (HHS, 2015). Full federal funding would then be reduced to 90% funding by 2020 (HHS, 2015). The decision to expand Medicaid was heavily influenced by politics. Because of the politicization of the ACA it is reasonable to assume that the opioid crisis played a very limited role in state decisions to expand Medicaid and can be seen as an exogenous policy change from this perspective. Some states decided to expand Medicaid immediately when eligible, while others waited months or years before expanding Medicaid (KFF, 2018).

The ACA required states that expanded Medicaid to offer Alternative Benefit Plans to the newly eligible expansion population. More specifically, Alternative Benefit Plans were required by the law to cover ten essential health benefits including treatment for SUDs (Grogan et al. 2016). However, the law does not specify what SUD treatment services must be offered. Medicaid expansion under the ACA has increased the significance of Medicaid with respect to SUDs. Bachrach et al. (2016) identify the population that qualifies for Medicaid under the expansion (income between 100%-138% of the poverty level) as more susceptible to SUDs than the general population: “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.” As of October 2017, over 74 million individuals were enrolled in Medicaid (Centers for Medicare & Medicaid Services, 2017). About 12% of adult Medicaid beneficiaries have a SUD (Center for Medicaid and CHIP Services, 2015). It is estimated that 1.6 million individuals with SUDs received health benefits as a result of the Medicaid expansion (Grogan et al., 2016).

2.1 Mechanisms

Of particular concern in this study is the impact of access to health care (though insurance) on opioid abuse and death. 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. Further, by 2010, 94% of users' selected heroin because prescription opioids were becoming too expensive and/or hard to obtain (Cicero et al., 2014). It is increasingly evident that opioids obtained through the American medical system have been abused 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 admission and a 7.4% increase in opioid deaths. Expanding Medicaid coverage may increase the supply and decrease the cost of prescription opioids (including opioid use disorder medications) in a given area. Through this channel, increasing health insurance coverage may lead to abuse of opioids (analgesics, illicit opioids or medications used to treat dependence on opioids).

The FDA has approved four opioid use disorder medications: methadone, buprenorphine, and naltrexone (oral and injectable). Buprenorphine is the most commonly prescribed opioid use disorder medication (Wen et al., 2017). These medications are used to relieve opioid withdrawal symptoms and can be used safely over long periods of time (months or years). Medication Assisted Treatment (MAT) has been shown to increase patient survival and patient retention in treatment, decrease opioid abuse and improve other outcomes (SAMHSA, 2015). However, FDA approved opioid use disorder medications can lead to overdose death. From 1999-2016, there were 66,592 methadone related overdose deaths (wonder CDC, ICD-10 code T40.3 Methadone, 2018). 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. Abuse 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 abuse 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). From 1999-2014, the rate of methadone related overdose death per 100,000 increased by 600% (Faul et al., 2017). Further, evidence points to Medicaid enrollees receiving methadone prescriptions at higher rates. 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.

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). Cost may not be the most important barrier to receiving treatment. More important may be a 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). Only a small percentage of the total population with SUDs 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 2015 (SAMHSA, 2016). By reducing the cost of treatment for opioid use disorder, Medicaid expansion may negatively impact opioid related mortality. Given the large population in the US addicted to opioids and the expense associated with treatment, individuals in states that expanded Medicaid are more likely to have access to treatment. Indeed, two recent studies have found significant increases in SUD medications prescribed in expanding states relative to non-expanding states. Maclean and Saloner (2017) find a 33% increase in prescriptions approved by the FDA to treat SUDs paid by Medicaid in expanding states compared to non-expanding states (Maclean and Saloner, 2017). 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.

Because the expansion of Medicaid may have both positive and negative impacts on opioids related deaths, I examine each subcategory of opioid related death available from the CDC multiple cause of death data individually. Using this disaggregation approach, I attempt to disentangle the effects of the Medicaid expansion on opioids that Medicaid may fund (opioid analgesics, methadone, etc.) and opioids that Medicaid will not fund (heroin, other illicit opioids). Maclean and Saloner (2017) test the impact of Medicaid expansion on total alcohol poisoning and drug-related overdose deaths and find no evidence of any such impact. Given that the Medicaid expansion may have effects in both directions within subcategories of total alcohol poisoning and drug-related overdose deaths, the effects of Medicaid expansions on poisoning deaths may be only statistically detectable when looking at individual categories of cause of death.

There are other mechanisms to consider. It may be that the passage of the ACA led to changes in the quality of care and/or other changes in benefits. Grogan et al. (2016) use the 2013-4 National Drug Abuse Treatment System Survey to identify which SUD treatments and medications are covered by Medicaid in each state. They find that Medicaid in all 50 states (and

D.C.) provided coverage for buprenorphine, but that only 31 (plus D.C.) state Medicaid programs covered all medications used to treat opioid use disorder as recommended by the ASAM. Grogan et al. (2016) identify 19 states in which methadone was not covered by the state Medicaid program. I incorporate this data into my identification strategy to more accurately estimate a treatment effect capturing the effect of expanding public insurance and access to MAT. Other nationwide changes associated with the ACA are controlled for with a year fixed effect.

2.2 The Opioid Epidemic

The opioid epidemic has been unfolding as these drastic changes to the American health care system have been implemented. Up until 1980, pain killers were generally prescribed for post-surgery pain, short-term pain, and for pain related to life threatening or terminal illnesses. Then our attitudes towards and uses for pain killers began to shift. In a 1980 letter to the editor in the New England Journal of Medicine, a reported study found less than one percent of patients prescribed pain killers became addicted (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 stared 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 2001, OxyContin was the bestselling narcotic pain reliever in the country. By 2010, OxyContin was the 15th ranked prescription by retail sales (Alpert et al., 2017). OxyContin became over-prescribed and widely available in the US. In many cases patients prescribed OxyContin (following a surgery or accident for example...) became addicted. 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 side (Alpert et al., 2017). There is growing evidence to suggest that these supply side policies have not decreased abuse of opioids, but rather has led to substitution among opioid users. Targeting the supply of prescription opioids may cause more harm than good given the availability of substitutes as the potency of opioid analgesics is controlled while potency of heroin or illicit fentanyl varies. Persistent abuse of OxyContin, led Purdue Pharma to reformulate the drug in 2010. OxyContin was typically abused by crushing pills and then injecting or inhaling (Alpert et al., 2017). Purdue Pharma initially introduced a pill that was harder to crush and abuse. Alpert et al. (2017) find that one additional percentage point of OxyContin abuse prior to reformation is associated with a decrease in OxyContin misuse of 0.8 percentage points and 2.5 additional heroin deaths (per 100,000). Evans et al. (2018) find that in states where heroin was more readily available, the reformulation of OxyContin did not reduce the combined heroin/opioid death rate.

Other state level policy changes have taken place and must be considered when examining the impact of the Medicaid expansion, including three types of laws intended to address the opioid epidemic: Prescription Drug Monitoring Programs (PDMPs), Naloxone Access Laws (NALs) and Good Samaritan Laws (GSLs). A PDMP is a centralized, electronic database designed to curb abuse of prescription drugs. PDMPs can regulate over-prescription resulting from prescriber behavior and patient behavior. Evidence regarding the effectiveness of PDMPs and other policies that seek to curb excessive opioid prescribing has been mixed. Bao et al. (2016) find that enacting a PDMP was associated with about a 30 percent 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 (2016) find that PDMPs have not affected prescribing rates unless they included "must access" clauses, which the majority of PDMPs do not have. Naloxone (also known by brand name Narcan) is a substance that can block or reverse the effects of opioids in the case of an overdose. NALs make it easier for medical professionals to prescribe and distribute Naloxone. 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 is associated with a 9 to 11 percent reduction in opioid-related deaths.

Increasing access to treatment may present a long term solution to the opioid crisis. While increasing access to Naloxone can help counteract the immediate effects of an opioid overdose, it cannot treat the underlying addiction. Katharine Q. Seelye of the New York Times writes: "many users overdose more than once, some multiple times, and each time, naloxone brings them back" (Seelye, 2016). In Middletown Ohio, City Councilman Dan Picard has even suggested capping the number of Narcan doses at 3 per user (Hoing, 2017). Increasing access to SUD treatment and mental health services should be a policy goal given changes in mortality and in substance abuse patterns. 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 in suicide (Case and Deaton, 2015). From 2000-2010, growth in opioid overdose deaths was driven by prescription opioid abuse (see Figures 1). From 2010-2015, additional growth in opioid overdose deaths was driven by heroin overdoses. Jones et al. (2015) find increases in heroin abuse among men, young adults (18-25), non-Hispanic whites and low income individuals. The demographic composition of this population is similar to the demographic composition of those eligible for expanded Medicaid coverage.

3. Data

The primary outcome variable of interest in this study is opioid related mortality. I examine a 17 year panel of data at the state, year level covering 1999-2016. The Wonder CDC multiple cause-of-death data contains detailed information regarding the cause of death including which type of opioids were involved in each death. 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 examine each of the above mentioned categories individually (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 6.2. It should be noted that any one overdose death could involve multiple ICD-10 codes (say heroin and other opioids were both used by an individual that later died). Next, I apply the same classifications to country level data (2005-2016). Country level mortality data were obtained from The National Association for Public Health Statistics and Information Systems (NAPHSIS).

Second, I consider outcome variables obtained from Medicaid State Drug Utilization data. I assemble a 10 year panel of data (2006-2016) containing methadone prescriptions reimbursed by Medicaid at the state, quarterly level. I consider 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 that aim to address the opioid epidemic including NALs, GSLs and PDMPs (hereafter referred to as other pertinent laws). Data regarding the implementation of GSLs comes from Rees et al. (2017). Data regarding NALs comes from the Policy Surveillance Program and from Rees et al. (2017). Data regarding PDMPs comes from the National Alliance for Model State Drug Laws. Given that these policies were designed to curb drug related overdose deaths, controlling for such changes in state law help eliminate any potential confounding impact resulting from policy change unrelated to the Medicaid expansions. Medicaid expansion dates were derived from the Kaiser Family Foundation (KFF) and Maclean and Saloner (2017). Unemployment data is from the Bureau of Labor Statistics (state and county level). Population data come from the NCHS Bridged-Race Population Estimates. State demographic data including the fraction of the state population that is white, black, ages 0-15, ages 16-35 and ages 36-64 come from the American Community Survey. Country level demographics were obtained from the NCHS Bridged-Race Population Estimates. State quarterly level population data were obtained from the Bureau of Economic Analysis Personal Income Summary (2010-2016).

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 population, the state unemployment rate, state demographics (age and race) and the changes in other pertinent laws described in section 2.2. 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 Medicaid expansion resulting from the ACA 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). [2] 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 (see for example, Kaestner et al., 2017). Five states and Washington D.C. expanded Medicaid prior to Jan 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 simply shifted from country 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 sample while D.C., MN, NJ and WA are dropped.

[2] In a few instances, I force Poisson models to converge after 500 iterations if convergence is not achieved.

Using survey data from Grogan et al. (2016) described in section 2.1, I estimate a model that takes into account differences in Medicaid benefits across states. Using this model I may more accurately identify the treatment effect of the expansion of Medicaid with respect to access to methadone. 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 opioid use disorder. Specifically, I estimate the following equation:

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

Here, MAT_s is an indicator variable equal to 1 if buprenorphine and methadone are covered by Medicaid in state s and equal to zero otherwise. $Other\ Expanding_{s,t}$ captures the expansion of Medicaid in states in which methadone is not covered by Medicaid. This model allows for a test of the treatment effect (expansion of Medicaid) only in states in which methadone is covered by Medicaid.

The ACA led to expansion of both public and private health insurance coverage. Other studies have used a difference-in-difference-in-differences (DDD) methodology to capture the impact of the public insurance expansion along with expansion of coverage in private insurance markets (Courtemanche et al., 2017; Courtemanche et al., 2018). The DDD strategy is used to bolster this study in two ways. First, the DDD results can help insure that results in the primary DD specification are not driven by differential trends. Second, the DDD strategy captures the treatment effect of health insurance expansion more generally (both public and private expansions). Following Courtemanche et al. (2017), I estimate the equation below:

$$\ln(\lambda_{s,t}) = \beta_1 + \beta_2\, Medicaid_{s,t} + \beta_3\, Uninsured_s * Post_t + \beta_4\, Medicaid_{s,t} * Uninsured_s * Post_t + X_{s,t}\,\gamma + \delta_t + \mu_s + + \varepsilon_{s,t} \qquad (4)$$

In equation (4), $Medicaid_{s,t}$ is the same measure described above. $Uninsured_s$ is the uninsured rate in state *s* in 2013 and $Post_t$ is an indicator equal to 1 in 2014 and subsequent years (equal to zero otherwise). I estimate equation (4) using state and country level data.

The validity of this identification strategy relies on the common trends assumption. I present event study analyses to examine the validity of this assumption. The event study analysis is 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. In my primary event study analysis, I also include late expanding states. I estimate the following event study:

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

Where $ES_{\,t}$ is an indicator variable equal to one in treatment state *s*, it 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.[3] Next, I consider an additional event study specification in which I drop all early and late expanding states. In this specification, the treatment group includes only states that expanded Medicaid in 2014 and the control group includes all non-expanding states.

[3] 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.

My primary specification uses state, year level data. I weight my regressions by the population in a given state and year. Next, I examine the robustness of these results to country, year level data. I examine how robust these results are to different functional forms and using unweighted models. First, I change the outcome of interest to a death rate, equal to the rate of opioid related deaths per 100,000 in state *s* and in year *t*. I estimate this model using OLS and use the same controls with the exception of the log population control. I estimate two transformations of the outcome variable: the natural log (LN) and inverse hyperbolic sine (IHS).[4] If the outcome variable of interest results in a ln(zero) transformation for some observations within a given subcategory of opioid related deaths, I add a small constant to the mortality rate before the transformation to avoid missing observations (equivalent to 1 death per 1,000,000 per state or country per year). As the dependent variable of interest is a count at the state year level, I present Poisson results as my primary specification.

5. Results

This study examines the impact of expanded health insurance access on opioid related mortality. Poisson results in table 2 suggest that the implementation of Medicaid expansion following the ACA has resulted in about a 30 percent reduction in heroin deaths and a 26 percent reduction in other unspecified narcotics related deaths. The magnitude of the finding is evident when considering the population weighted mean number of heroin related deaths (202 per state per year) and other unspecified narcotics related overdose deaths (113 per state per year). The impact of Medicaid expansion varies by each subcategory of opioid related overdose death. Expansion of Medicaid is associated with a 14.5 percent increase in methadone related deaths.

[4] IHS transformation is considered given concerns about the LN transformation in the case that the outcome variable is zero or close to zero

Methadone represents a smaller portion of total opioid deaths than heroin, the population weighted mean number of methadone related overdose deaths is about 140 per state year. Grouping each subcategory, I find that the Medicaid expansion had a negative impact on opioid deaths though the coefficient is not statically significant. This may be explained by opposite effects by subcategory. For example, my results suggest that the expansion of Medicaid would lead to a decrease of 61 heroin related deaths and an increase of 20 methadone related deaths in a given state, in a given year.[5] Increases in methadone related overdose deaths may be related to increases in methadone treatment for opioid use disorder in expanding states, though methadone is also prescribed for chronic pain as well.

Table 3 points to access to MAT through insurance as a crucial channel in reducing heroin and other opioid related deaths while also driving increases in methadone related deaths. Little effect is observed in expanding states in which Medicaid does not cover methadone (see section 6 for additional discussion). Results in table 4 were estimated using equation (4) above. The coefficient β_3 captures the private portion of insurance expansion following the ACA. The private expansion reduced opioid deaths by about 3.5 percent and heroin and other opioid deaths by 4-4.5 percent. Estimates of β_3 and β_4 are both negative in 5 of 6 specifications, suggesting that overall, expanded health insurance coverage is alleviating the opioid epidemic. This result appears robust with using county level data (table A9) as these coefficients remain relatively stable. Comparing β_2 and β_3 reveals that the expansion of Medicaid is playing a more important role than the private market expansion as β_2 is larger in magnitude. In terms of total ACA coverage gains by 2017, Medicaid enrollment had grown by about 17 million, while about 10 million individuals gained coverage through the new state or federal marketplaces (KFF, 2017).

[5] A back of the envelope calculation obtained by multiplying the estimated treatment effect times the population weighted mean number of deaths

5.1 Robustness

In order to test robustness to functional form, I present OLS and negative binomial regression results, as the distributional assumptions of the Poisson model may be too restrictive (Cameron and Trivedi, 2001). OLS (table 5) and negative binomial (table A8) results show that my findings are relatively robust to different distributional assumptions, though the OLS results are less precise. Results in table 7 show the robustness of my finding with respect to methadone related deaths using county level data and across different specifications.[6] Using county level data, both Poisson and OLS models offer similar estimates of about an 18-9 percent increase in methadone related deaths resulting from the expansion of Medicaid (see columns 2 and 4 in table 7). Table 8 shows the results of the county level estimates with respect to heroin and other unspecified narcotics using estimating equations (2) and (3). Again, state level results appear robust and reductions in heroin related deaths are driven by expansion of Medicaid in states in which Medicaid recipients have access to all opioid use disorder medications.

I present population weighted models as my primary specification. I test the robustness of these results by estimating unweighted models. My main results are robust when weighted by population (table 2) or unweighted (table A2). As an additional robustness check, I re-estimate the treatment effect dropping each treatment state individually (all early expanding states are included in this sample). For heroin deaths (table A3), the estimated treatment effect remains relatively stable with the exception of the specification in which California is dropped.[7] For methadone related deaths, the estimated treatment effect remains stable compared to the baseline (table A4) in all specifications. As a placebo, I test if this model can explain demographic

[6] High dimensional fixed effect county level Poisson estimates were generated using the Stata command poi2hdfe developed in Guimaraes and Portugal (2010). It should be noted that weights cannot be used with this command and counties with zero deaths in each sample year were dropped from these models

[7] 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)

changes by state and year (see table A6) but find no significant results. Finally, I present state and county level results together in table A10, restricting the state sample such that state and county level data cover the same time period.

5.2 Common Trends and Validity of Identification Strategy

I present event study analyses to examine the differential trends between treatment and control states. While the counterfactual is un-observable for the treatment group post treatment, 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 (see table 9). Second, I drop all early and late expanding states (figures 4-6) and include state specific linear time trends. In this specification, the event year is 2014. The treatment group includes only states that expanded Medicaid in 2014 and the control group includes all non-expanding states.

Figure 2 reveals no visible pre-trends with respect to heroin related overdose deaths. Careful examination of the methadone related deaths event studies (figure 3) reveals changes in the pre-period though a treatment effect appears visible in the post-period. This pre-policy change appears driven in part by a spike in methadone deaths in California in 2009 (see figure A1). In figure 4, all early and late expanding states are dropped: pre-trends no longer appear problematic. In Figure 5 and 6, again, no pre-trends appear with respect to heroin and other narcotics related deaths. I re-estimate equation (2), adding a dummy variable that is a 2 year lead to the policy change in expansion states (equivalent to the event study variable for year $t = -2$, see table A7). This 2 year lead is not statically significant except for the methadone outcome, passing the placebo test in 5 of 6 specifications.

6 Discussion of Mechanisms

Maclean and Saloner (2017) find a 33% increase in prescriptions used to treat opioid use disorder in expanding states relative to non-expanding states. Their results suggest that the expansion of Medicaid has led to increased demand for prescriptions used to treat opioid use disorder, most likely because of cost reduction. These medications are prescribed to help with dependence on opioids as they lead to better health outcome compared to untreated patients with opioid use disorder. Reductions in opioid deaths resulting from Medicaid expansion are most likely explained by these increases in Medicaid funded prescriptions for opioid use disorder and increased access to treatment.

Maclean and Saloner (2017) do not include methadone in their study as methadone is prescribed for uses other than treatment of opioid use disorder (chronic pain). Results in table 6 show that the Medicaid expansion was associated with a 21-40 percent increase in methadone prescriptions reimbursed by Medicaid depending on the outcome considered (number of prescriptions, amount reimbursed or units reimbursed). As expected, the coefficient of interest increases in magnitude as estimated by equation (3). In other words, methadone prescriptions increased in states in which Medicaid covers methadone and Medicaid was expanded. These results could be suggestive of increased utilization of methadone therapy for opioid use disorder in expanding states relative to non-expanding states. However, methadone is commonly prescribed for chronic pain, particularly in cancer patients. So these results do not directly imply increased utilization of methadone treatment for opioid use disorder.

Table 3 points to both the benefits and dangers of expanding access to MAT. Statistically significant decreases in heroin and other opioid deaths were driven by the expansion of Medicaid in states in which both buprenorphine and methadone are covered by Medicaid. At the same time, increases in methadone related deaths were driven by states in which Medicaid was expanded and methadone is covered by Medicaid. These states also experience significant increases in deaths from synthetic opioids (ICD-10 code T40.4: Fentanyl, Propoxyphene, Meperidine, Buprenorphine). While likely driven by large increases in fentanyl use, increasing access to buprenorphine might be contributing. The Tennessee Department of Health recently found that deaths were associated with buprenorphine abuse and use of buprenorphine in concurrence with other prescription or illicit drugs (Tennessee Department of Health, 2018).

6.1 Measurement Error

Measurement error presents a major 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). I consider deaths classified by ICD-10 code T50.9 in table A5.

Comparing tables 4 and A5, 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

My results build on recent papers from Maclean and Saloner (2017) and Wen et al. (2017). Maclean and Saloner (2017) find no reduction in total alcohol and drug poisoning/overdose deaths in expanding states relative to non-expanding states. But I find statistically significant impacts in subsets of total alcohol and drug poisoning/overdose deaths. Methadone and buprenorphine are the two most commonly prescribed medications for opioid use disorder. Maclean and Saloner (2017) and Wen et al. (2017) present strong evidence of increased demand for buprenorphine and other substance use disorder medications within states that expanded Medicaid. I expand further on their research by presenting evidence of increases in methadone prescriptions funded by Medicaid in expanding states. This is the most likely channel (expanded access to treatment and MAT for opioid use disorder) through which the expansion of Medicaid may reduce opioid related deaths. However, increasing access to prescription opioids of any type opens up the possible abuse and/or illicit resale of such prescriptions. Increases in methadone prescriptions increase the probability that methadone is abused or resold on the illicit, non-medical market and may explain the increases in methadone deaths in expanding states documented in this study.

Reducing out of pocket cost and increasing access to treatment (inpatient, outpatient and prescriptions for opioid use disorder) may be the most effective way to combat the opioid crisis. Frank and Glied (2017) estimate that 220,000 Americans with an opioid use disorder would lose some of all of their insurance coverage as a result of a repeal of the ACA (including behavioral health provisions). Mounting evidence points to the shortcoming of other policies implemented to address the crisis. Naloxone has prevented many potential opioid overdose deaths but does not treat addiction. Restricting the supply of opioids and creating abuse deterrent versions of prescription opioids has led to unintended consequences given the availability of substitutes. This mounting evidence of substitution among opioid users points to the need for policy to move away from the supply side approach. In 2015, an estimated 441,000 non-elderly adults were uninsured and addicted to opioids (Zur, 2017). For these individuals, effective treatment may simply be too costly to obtain. This study points to the importance of expansion of coverage and reduction of cost for SUD treatment as effective policy in combatting the opioid epidemic.

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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	0.12	0.32
County Level (2005-2016)		
All Opioids	74.26	114.39
All Opioids rate per 100k	7.61	7.35
Heroin (T40.1)	22.39	48.01
Heroin rate per 100k	1.83	3.01
Other Opioids (T40.2)	28.09	47.44
Other Opioids rate per 100k	2.98	3.57
Methadone (T40.3)	10.01	15.10
Methadone rate per 100k	1.34	2.10
Synthetic Opioids (T40.4)	10.87	32.62
Synthetic Opioids rate per 100k	1.38	3.13
Other/Unspecified Narcotics (T40.6)	10.81	42.86
Other/Unspecified Narcotics rate per 100k	0.80	1.74
Medicaid Expansion	0.17	0.37

Notes: Early Expanding States dropped except CA and CT

Table 2: Poisson Results, State Level, 1999-2016				Mean of dependent variable
Panel A: Heroin				201.86
Medicaid Expansion	-0.445**	-0.312**	-0.355**	
	(0.219)	(0.149)	(0.145)	
Coefficient Interpretation	-0.36	-0.27	-0.30	
Panel B: Methadone				140.14
Medicaid Expansion	0.367***	0.194***	0.135*	
	(0.0827)	(0.0721)	(0.0723)	
Coefficient Interpretation	0.44	0.21	0.14	
Panel C: Other Narcotics				112.89
Medicaid Expansion	-0.284**	-0.240*	-0.300**	
	(0.130)	(0.141)	(0.124)	
Coefficient Interpretation	-0.25	-0.21	-0.26	
Panel D: All Opioids				819.74
Medicaid Expansion	-0.113	-0.0238	-0.0370	
	(0.114)	(0.0693)	(0.0711)	
Coefficient Interpretation	-0.11	-0.02	-0.04	
Controls: Population	Yes	Yes	Yes	
Age and Demographics	No	Yes	Yes	
Unemployment Rate	No	Yes	Yes	
Other Pertinent Laws	No	No	Yes	
N	846	846	846	

Notes: Population weighted estimates. Models include year fixed effect and state fixed effect. Pertinent Laws include Naloxone Access Laws, Good Samaritan Laws and Prescription Drug Monitoring Programs. Standard errors in parentheses are clustered at the state level. * p<0.10, ** p<0.05, *** p<0.01

Table 3: Medicaid Expansion Interaction, State Level, 1999-2016

	All Opioids	Heroin	Other Opioids	Methadone	Synthetic	Other Narcotics
Medicaid*MAT	-0.0269	-0.388**	-0.184*	0.189***	0.291*	-0.0132
	(0.0915)	(0.173)	(0.0995)	(0.0671)	(0.158)	(0.146)
Coefficient Interpretation	-0.03	-0.32	-0.17	0.21	0.34	-0.01
Other Expanding States	-0.00428	-0.0122	-0.0126	0.126	0.0833	-0.679*
	(0.0787)	(0.191)	(0.133)	(0.126)	(0.145)	(0.403)
Coefficient Interpretation	0.00	-0.01	-0.01	0.13	0.09	-0.49
Mean of Dependent	819.74	201.86	363.43	140.14	136.49	112.89
N	846	846	846	846	846	846

Notes: Population weighted estimates. Models include year fixed effect and state fixed effect. 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: Poisson DD and DDD, State Level, 1999-2016

	All Opioids	Heroin	Other Opioids	Methadone	Synthetic Opioids	Other Narcotics
Panel A: DD						
Medicaid Expansion	-0.0238	-0.312**	-0.159*	0.194***	0.260*	-0.240*
	(0.0693)	(0.149)	(0.0958)	(0.0721)	(0.149)	(0.141)
Coefficient Interpretation	-0.02	-0.27	-0.15	0.21	0.30	-0.21
Panel B: DDD						
Medicaid Expansion	-0.0425	-0.279*	-0.227***	0.123*	0.545**	-0.182
	(0.0891)	(0.163)	(0.0777)	(0.0698)	(0.221)	(0.131)
Coefficient Interpretation	-0.04	-0.24	-0.20	0.13	0.72	-0.17
Uninsured Rate	-0.0355***	-0.0416*	-0.0455***	-0.0166	-0.0361	-0.0300
	(0.0106)	(0.0221)	(0.0163)	(0.0158)	(0.0283)	(0.0193)
Coefficient Interpretation	-0.03	-0.04	-0.04	-0.02	-0.04	-0.03
Interaction	-0.0138***	-0.0231*	-0.00990	0.00234	-0.0491***	-0.0244**
	(0.00415)	(0.0128)	(0.00636)	(0.00528)	(0.00967)	(0.0124)
Coefficient Interpretation	0.01	-0.02	-0.01	0.00	-0.05	-0.02
Mean of dependent variable	819.74	201.86	362.43	140.14	136.49	112.89
Controls:						
Population	Yes	Yes	Yes	Yes	Yes	Yes
Age and Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Unemployment Rate	Yes	Yes	Yes	Yes	Yes	Yes
N	846	846	846	846	846	846

Notes: Population weighted estimates. Models include year fixed effect and state fixed effect. Standard errors in parentheses are clustered at the state level. * p<0.10, ** p<0.05, *** p<0.01

Table 5: OLS, State Level, 1999-2016

	All Opioids	Heroin	Other Narcotics	Methadone	All Opioids	Heroin	Other Narcotics	Methadone
Panel A: Expansion								
Medicaid Expansion	0.0118	0.0245	-0.152*	0.177**	0.000248	-0.147	-0.254**	0.170**
	(0.147)	(0.234)	(0.0897)	(0.0669)	(0.151)	(0.289)	(0.125)	(0.0641)
Panel B: Interaction								
Medicaid*MAT	-0.0481	-0.107	-0.142*	0.193**	-0.0640	-0.338	-0.275**	0.185**
	(0.170)	(0.258)	(0.0789)	(0.0729)	(0.175)	(0.306)	(0.124)	(0.0698)
Other Expanding States	0.211**	0.463**	-0.183	0.124	0.214**	0.485*	-0.182	0.119
	(0.0963)	(0.221)	(0.297)	(0.0990)	(0.100)	(0.264)	(0.363)	(0.0950)
Mean of dependent variable before transformation	6.76	1.57	0.96	1.21	6.76	1.57	0.96	1.21
Transformation of dependent	IHS	IHS	IHS	IHS	LN	LN	LN	LN
N	846	846	846	846	846	846	846	846

Notes: State level population weighted estimates. Dependent variable: death rate per 100,000. Controls include Age and Demographics and Unemployment Rate. Models include year fixed effect and state fixed effect. Standard errors in parentheses are clustered at the state level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 6: Methadone - Medicaid State Drug Utilization Data

Dependent	Log Number of Prescriptions	Log Number of Prescriptions	Log Medicaid Amount Reimbursed	Log Medicaid Amount Reimbursed	Log Units Reimbursed	Log Units Reimbursed
Panel A: Expansion						
Medicaid Expansion	0.405***	0.304**	0.357**	0.181	0.315***	0.215*
	(0.130)	(0.117)	(0.144)	(0.160)	(0.113)	(0.117)
Panel B: Interaction						
Medicaid*MAT	0.572***	0.377**	0.533***	0.223	0.447***	0.268*
	(0.149)	(0.141)	(0.178)	(0.187)	(0.129)	(0.139)
Other Expanding	-0.0463	-0.0269	-0.109	-0.0112	0.00172	0.0256
States	(0.149)	(0.191)	(0.185)	(0.201)	(0.124)	(0.146)
Population Weighted	No	Yes	No	Yes	No	Yes
Mean of Dependent Before Transformation	5,183.41	5,183.41	107,727.00	107,727.00	569,722.10	569,722.10
N	2,009	2,009	1,857	1,857	1,475	1,475

Notes: Medicaid State Drug Utilization data 2006-2016, state, quarter level. Models include quarter fixed effect, state fixed effect and control for the natural log of population. Quarterly Population data come from the Bureau of Economic Analysis Personal Income Summary 2010-2016. Annual Population data used as a proxy (2006-2010) 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: County Level Robustness, Methadone Deaths, 2005-2016

Panel A: Expansion						
Medicaid Expansion	0.261***	0.178**	0.241**	0.174**	0.152**	0.108*
	(0.0874)	(0.0724)	(0.0964)	(0.0807)	(0.0687)	(0.0560)
Panel B: Interaction						
Medicaid*MAT	0.290***	0.200***	0.231**	0.148*	0.144*	0.0903
	(0.0876)	(0.0711)	(0.102)	(0.0773)	(0.0731)	(0.0551)
Other Expanding	0.0961	0.0804	0.278	0.249*	0.179	0.158*
States	(0.223)	(0.184)	(0.169)	(0.147)	(0.107)	(0.0910)
Mean of dependent variable before transformation	10.00	10.00	1.34	1.34	1.34	1.34
Model	Poisson	Poisson	OLS	OLS	OLS	OLS
Population Weight	No	No	Yes	Yes	Yes	Yes
Controls:						
Population	Yes	Yes	No	No	No	No
Age and Demographics	No	Yes	No	Yes	No	Yes
Unemployment Rate	No	Yes	No	Yes	No	Yes
Transformation of Dependent	None	None	LN	LN	IHS	IHS
N	25,798	25,798	35,877	35,877	35,877	35,877

Notes: Models include county fixed effect and year fixed effect. Standard errors in parentheses are clustered at the state level. * p<0.10, ** p<0.05, *** p<0.01

Table 8: County Level Robustness - Heroin and Other Unspecified Narcotics Deaths, 2005-2016

	Heroin	Heroin	Heroin	Other Unspecified Narcotics	Other Unspecified Narcotics	Other Unspecified Narcotics
Panel A: Expansion						
Medicaid Expansion	-0.149	-0.140	-0.203	-0.338**	-0.212	-0.229*
Coefficient Interpretation	(0.149)	(0.136)	(0.134)	(0.155)	(0.148)	(0.125)
	-0.14	-0.13	-0.18	-0.29	-0.19	-0.20
Panel B: Interaction						
Medicaid*MAT	-0.287*	-0.286**	-0.338**	-0.237***	-0.129	-0.162*
Coefficient Interpretation	(0.160)	(0.139)	(0.140)	(0.0906)	(0.100)	(0.0953)
	-0.25	-0.25	-0.29	-0.21	-0.12	-0.15
Other Expanding States	0.246*	0.242*	0.136	-0.756*	-0.538	-0.500
	(0.141)	(0.144)	(0.161)	(0.454)	(0.391)	(0.326)
Mean of dependent variable	22.39	22.39	22.39	10.81	10.81	10.81
Controls:						
Population	Yes	Yes	Yes	Yes	Yes	Yes
Age and Demographics	No	Yes	Yes	No	Yes	Yes
Unemployment Rate	No	Yes	Yes	No	Yes	Yes
Other Pertinent Laws	No	No	Yes	No	No	Yes
N	18,449	18,449	18,449	17,796	17,796	17,796

Notes: Un-weighted Poisson estimates. Models include county fixed effect and year fixed effect. Pertinent Laws include Naloxone Access Laws, Good Samaritan Laws and Prescription Drug Monitoring Programs. Standard errors in parentheses are clustered at the state level. * p<0.10, ** p<0.05, *** p<0.01

Table 9: Medicaid Expansion under the ACA

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 Sloner (2017)

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

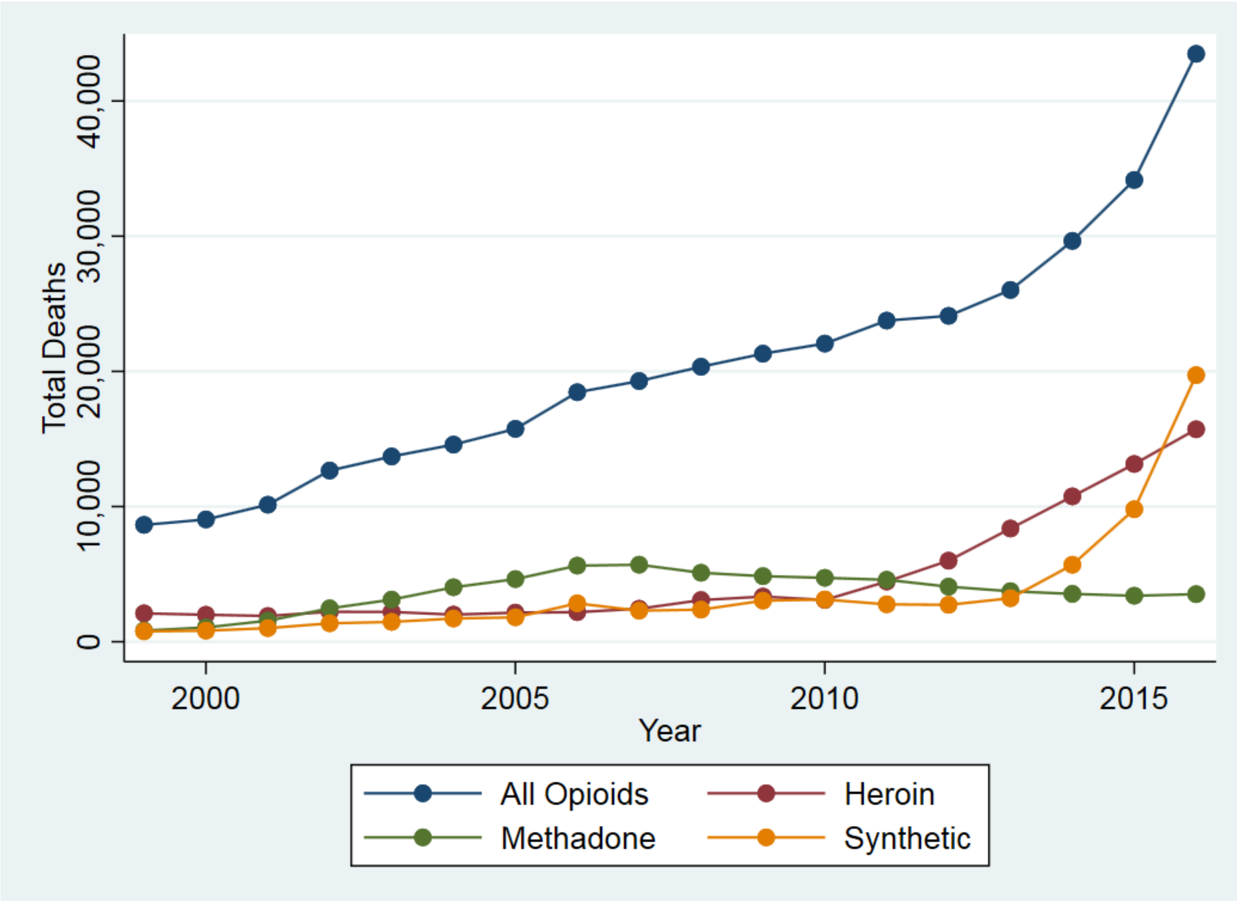
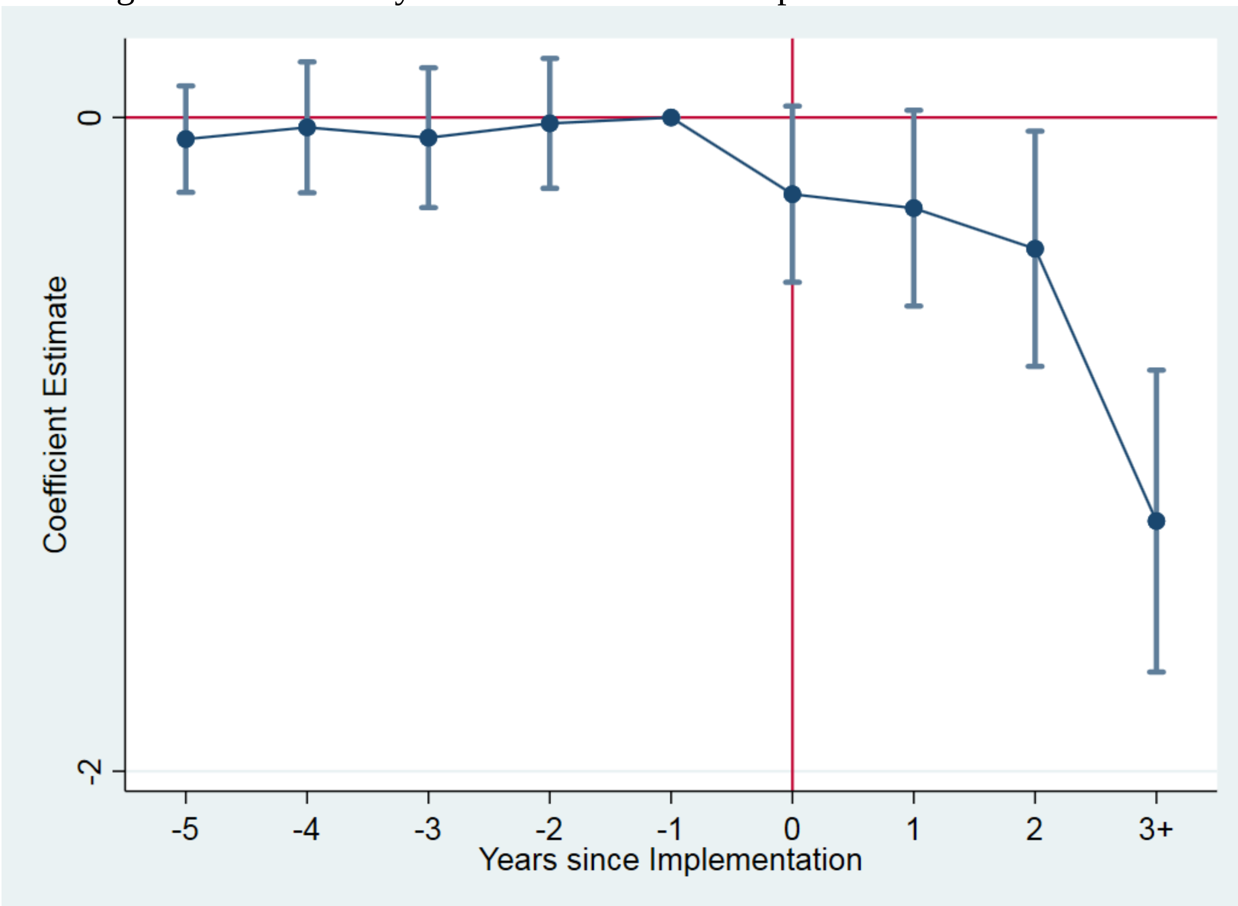
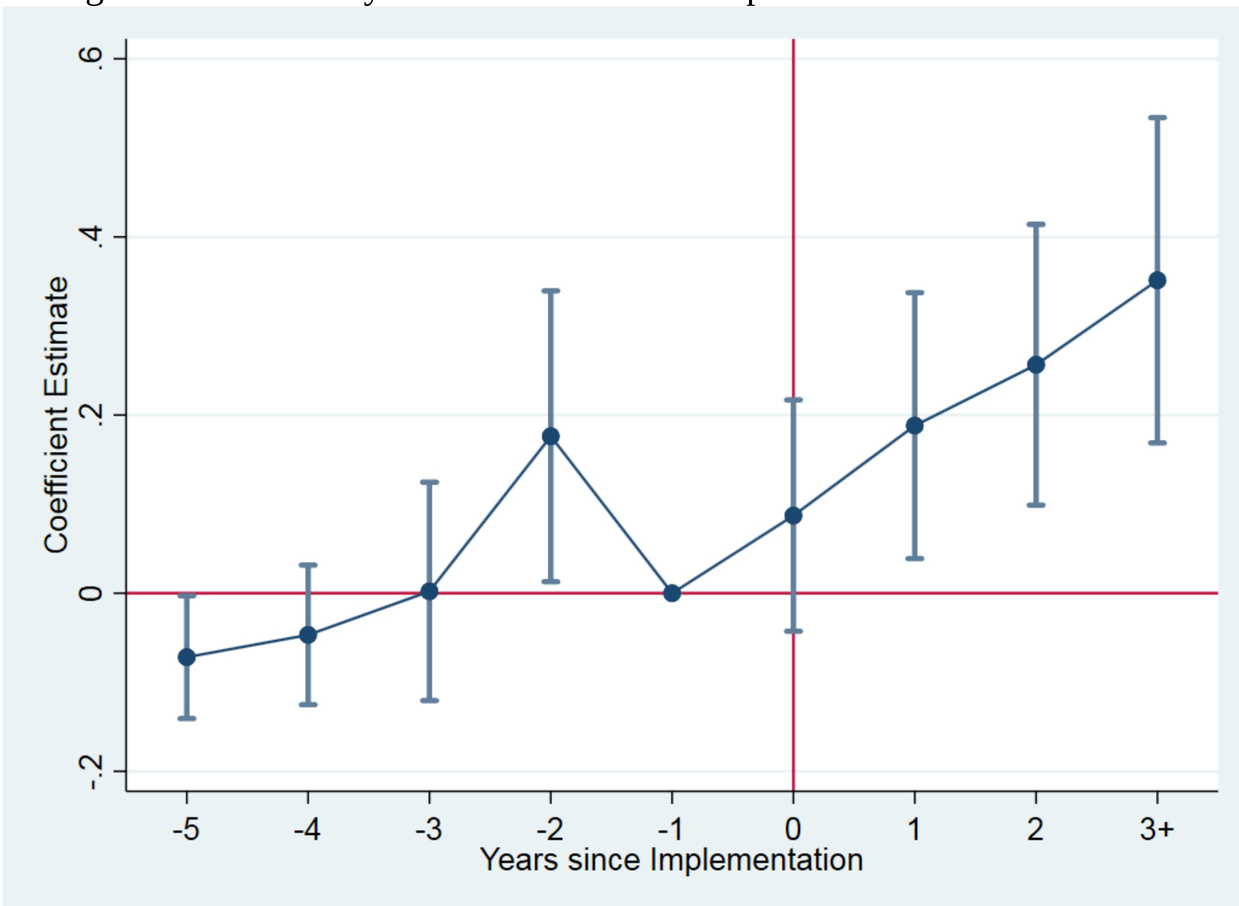


Figure 2: Event Study - Effect of Medicaid Expansion on Heroin Deaths



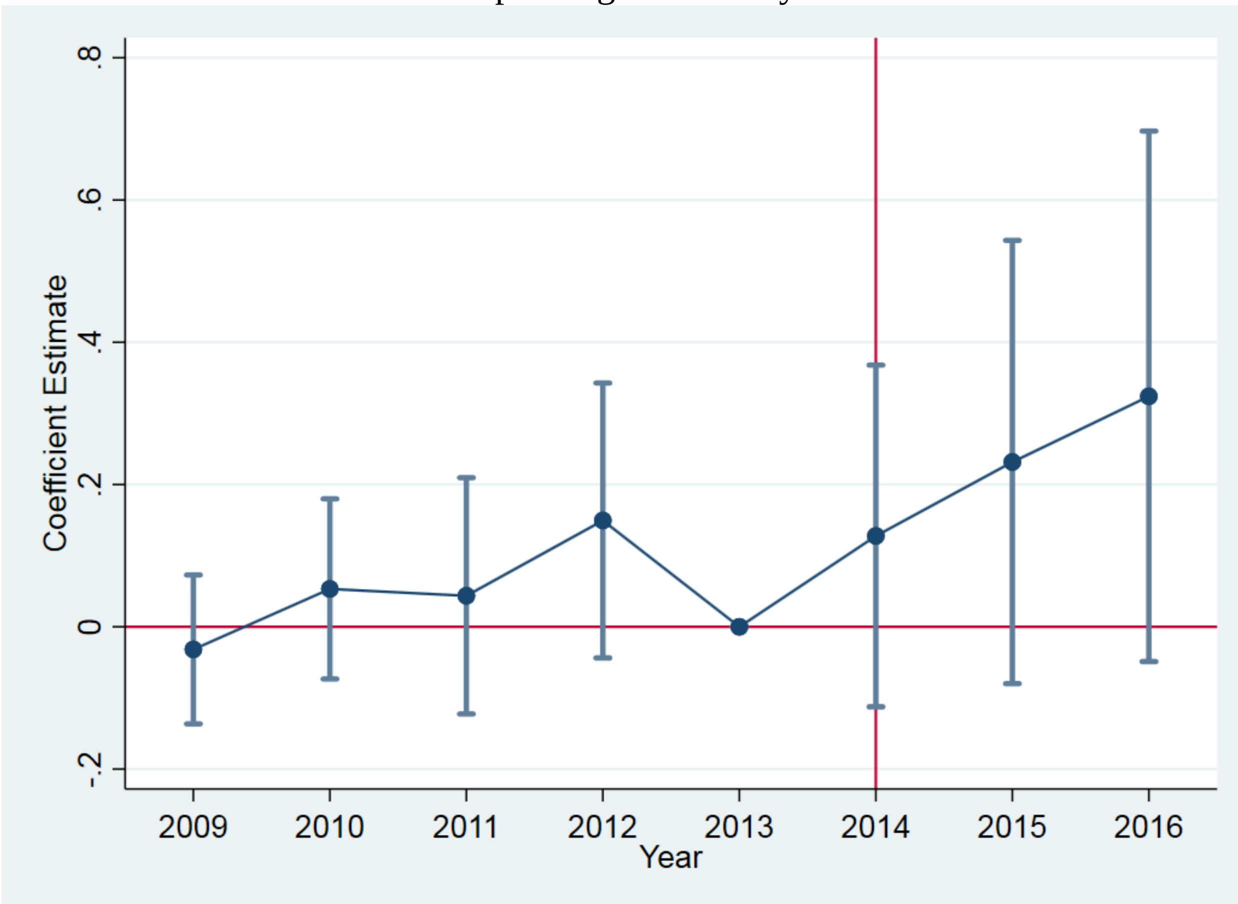
Notes: Poisson coefficient estimates. Controls include population, age, race, unemployment rate and pertinent laws. Model includes year fixed effect, and state fixed effect. Weighted by population, standard errors are clustered at the state level.

Figure 3: Event Study - Effect of Medicaid Expansion on Methadone Deaths



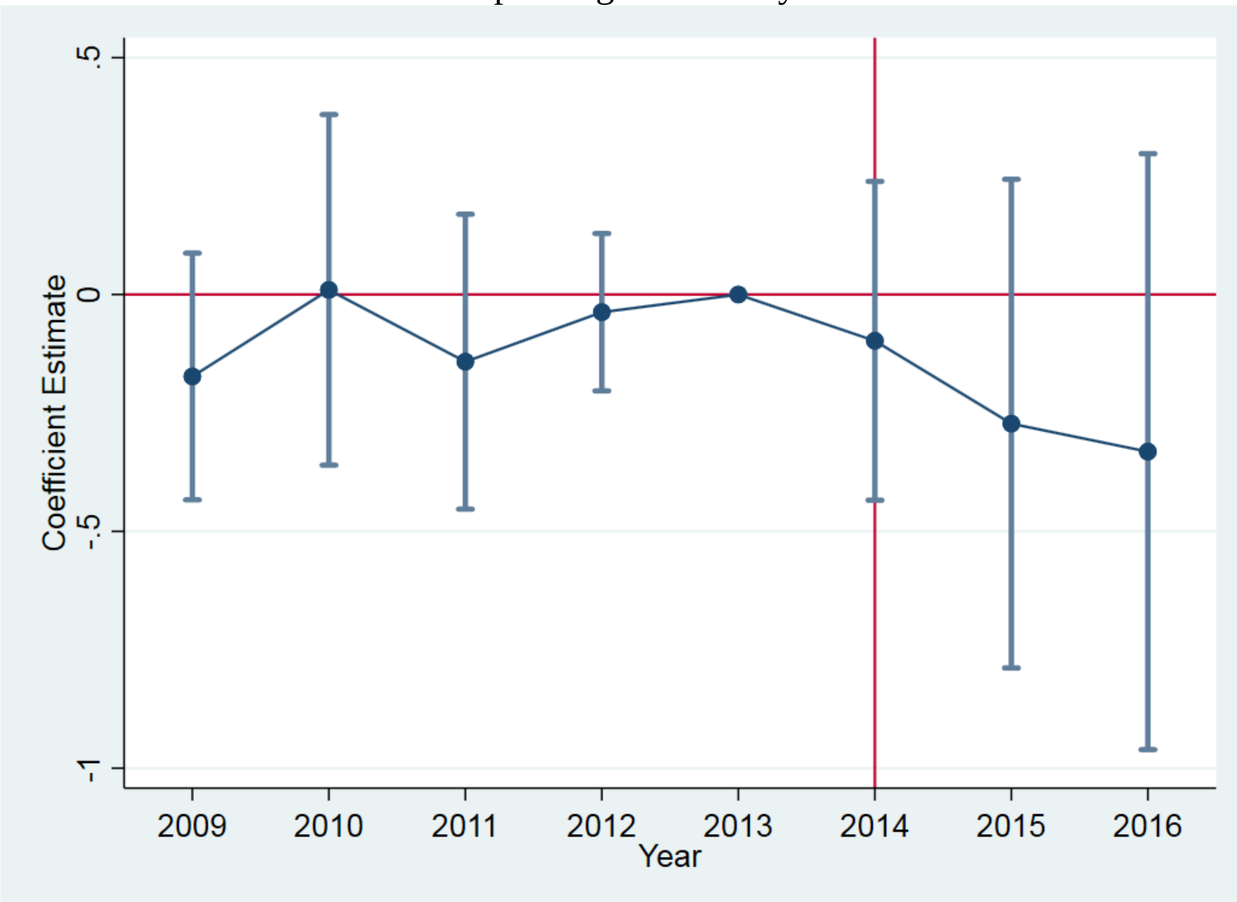
Notes: Poisson coefficient estimates. Controls include population, age, race, unemployment rate and pertinent laws. Model includes year fixed effect, and state fixed effect. Weighted by population, standard errors are clustered at the state level.

Figure 4: Event Study - Effect of Medicaid Expansion on Methadone Deaths: 2014 Expanding States Only



Notes: Poisson coefficient estimates. Controls include state specific linear time trends, population and the unemployment rate. Model includes year fixed effect and state fixed effect. Weighted by population, standard errors are clustered at the state level.

Figure 5: Event Study - Effect of Medicaid Expansion on Heroin Deaths: 2014 Expanding States Only



Notes: Poisson coefficient estimates. Treatment group includes only states that expanded Medicaid in 2014. Control group includes all non-expanding states. Controls include state specific linear time trends, population, age, race and the unemployment rate. Model includes year fixed effect and state fixed effect. Weighted by population, standard errors are clustered at the state level.

Figure 6: Event Study - Effect of Medicaid Expansion on Other/Unspecified Narcotics Deaths: 2014 Expanding States Only

Notes: Dependent variable - other/unspecified narcotics deaths (ICD-10 code T40.6). Poisson coefficient estimates. Treatment group includes only states that expanded Medicaid in 2014. Control group includes all non-expanding states. Controls include state specific linear time trends, population, age, race and the unemployment rate. Model includes year fixed effect and state fixed effect. Weighted by population, standard errors are clustered at the state level.

10. Appendix

Table A1: Unweighted Summary Statistics

Variable	Mean	Std. Dev
State Level (1999-2016)		
All Opioids	404.23	471.25
All Opioids rate per 100k	7.35	5.35
Heroin (T40.1)	93.96	172.50
Heroin rate per 100k	1.44	1.97
Other Opioids (T40.2)	172.81	212.55
Other Opioids rate per 100k	3.33	2.94
Methadone (T40.3)	72.28	82.89
Methadone rate per 100k	1.42	1.06
Synthetic Opioids (T40.4)	74.89	170.83
Synthetic Opioids rate per 100k	1.42	2.55
Other/Unspecified Narcotics (T40.6)	57.38	96.13
Other/Unspecified Narcotics rate per 100k	1.00	1.29
Medicaid Expansion	0.10	0.30
County Level (2005-2016)		
All Opioids	7.32	27.00
All Opioids rate per 100k	6.06	11.31
Heroin (T40.1)	1.76	10.09
Heroin rate per 100k	0.78	2.58
Other Opioids (T40.2)	2.87	10.55
Other Opioids rate per 100k	2.82	5.89
Methadone (T40.3)	1.29	4.62
Methadone rate per 100k	1.33	7.12
Synthetic Opioids (T40.4)	1.33	8.32
Synthetic Opioids rate per 100k	1.19	3.66
Other/Unspecified Narcotics (T40.6)	0.77	6.95
Other/Unspecified Narcotics rate per 100k	0.44	2.21
Medicaid Expansion	0.10	0.30

Notes: Early Expanding States dropped except CA and CT

Table A2: Poisson Results, State Level, 1999-2016

Panel A: Heroin			
Medicaid Expansion	-0.266	-0.196	-0.215
	(0.173)	(0.148)	(0.143)
Mean of dependent variable	93.96	93.96	93.96
Panel B: Methadone			
Medicaid Expansion	0.268***	0.163**	0.145**
	(0.0882)	(0.0806)	(0.0728)
Mean of dependent variable	72.28	72.28	72.28
Panel C: Other Narcotics			
Medicaid Expansion	-0.325**	-0.316**	-0.343**
	(0.144)	(0.144)	(0.136)
Mean of dependent variable	57.38	57.38	57.38
Panel D: All Opioids			
Medicaid Expansion	-0.0229	0.00244	-0.00470
	(0.0865)	(0.0716)	(0.0687)
Mean of dependent variable	404.23	404.23	404.23
Controls:			
Population	Yes	Yes	Yes
Age and Demographics	No	Yes	Yes
Unemployment Rate	No	Yes	Yes
Other Pertinent Laws	No	No	Yes
N	864	864	864

Notes: Unweighted estimates. Models include year fixed effect and state fixed effect. Pertinent Laws include Naloxone Access Laws, Good Samaritan Laws and Prescription Drug Monitoring Programs. Standard errors in parentheses are clustered at the state level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table A3: Drop Each Individual Treatment State - Heroin

		Early Expanding States						Jan 1st 2014			
State	Baseline	CA	CT	D.C.	MN	NJ	WA	AZ	AR	CO	DE
Dropped	-0.304**	-0.0174	-0.300**	-0.302**	-0.311**	-0.296**	-0.313**	-0.331**	-0.304**	-0.312**	-0.304**
	(0.144)	(0.146)	(0.145)	(0.143)	(0.144)	(0.145)	(0.148)	(0.143)	(0.144)	(0.146)	(0.144)
N	918	900	900	900	900	900	900	900	900	900	900

	Jan 1st 2014										
State	HI	IL	IA	KY	MD	MA	MI	NV	NM	NY	ND
Dropped	-0.304**	-0.306**	-0.304**	-0.308**	-0.312**	-0.313**	-0.298**	-0.308**	-0.303**	-0.288**	-0.304**
	(0.144)	(0.126)	(0.144)	(0.145)	(0.144)	(0.142)	(0.144)	(0.146)	(0.144)	(0.134)	(0.144)
N	900	900	900	900	900	900	900	900	900	900	900

	Jan 1st 2014					Late Expanding States					
State	OH	OR	RI	VT	WV	NH	AK	IN	MT	LA	PA
Dropped	-0.298**	-0.294**	-0.303**	-0.304**	-0.304**	-0.302**	-0.303**	-0.307**	-0.304**	-0.299**	-0.377***
	(0.150)	(0.144)	(0.144)	(0.144)	(0.144)	(0.144)	(0.144)	(0.146)	(0.144)	(0.144)	(0.130)
N	900	900	900	900	900	900	900	900	900	900	900

Notes: Dependent variable - heroin deaths. Population weighted Poisson estimates. Controls: log population, unemployment, age and race controls. Models include year fixed effect and state fixed effect. Standard errors in parentheses are clustered at the state level. * p<0.10, ** p<0.05, *** p<0.01

Table A4: Drop Each Individual Treatment State - Methadone

		Early Expanding States						Jan 1st 2014			
State	Baseline	CA	CT	D.C.	MN	NJ	WA	AZ	AR	CO	DE
Dropped	0.194***	0.174*	0.197***	0.194***	0.178***	0.194***	0.212***	0.190***	0.196***	0.190***	0.194***
	(0.0703)	(0.105)	(0.0708)	(0.0703)	(0.0685)	(0.0698)	(0.0745)	(0.0699)	(0.0708)	(0.0698)	(0.0702)
N	918	900	900	900	900	900	900	900	900	900	900

	Jan 1st 2014										
State	HI	IL	IA	KY	MD	MA	MI	NV	NM	NY	ND
Dropped	0.194***	0.178***	0.195***	0.201***	0.181***	0.196***	0.193***	0.198***	0.193***	0.216***	0.194***
	(0.0703)	(0.0675)	(0.0707)	(0.0710)	(0.0652)	(0.0702)	(0.0745)	(0.0697)	(0.0704)	(0.0815)	(0.0703)
N	900	900	900	900	900	900	900	900	900	900	900

	Jan 1st 2014					Late Expanding States					
State	OH	OR	RI	VT	WV	NH	AK	IN	MT	LA	PA
Dropped	0.204***	0.197***	0.194***	0.194***	0.196***	0.194***	0.194***	0.195***	0.194***	0.189***	0.190***
	(0.0721)	(0.0709)	(0.0704)	(0.0703)	(0.0700)	(0.0703)	(0.0703)	(0.0711)	(0.0703)	(0.0702)	(0.0711)
N	900	900	900	900	900	900	900	900	900	900	900

Notes: Dependent variable - Methadone deaths. Population weighted Poisson estimates. Controls: log population, unemployment, age and race controls. Models include year fixed effect and state fixed effect. Standard errors in parentheses are clustered at the state level. * p<0.10, ** p<0.05, *** p<0.01

Table A5: T50.9 (Other and unspecified drugs, medicaments and biological substances) , 1999-2016

	All Opioids & T50.9	All Opioids & T50.9	All Opioids & T50.9
Panel A: DD			
Medicaid Expansion	-0.054	0.0246	0.0167
	(0.0848)	(0.0475)	(0.047)
Panel B: DDD			
Medicaid Expansion	-0.062	-0.0199	-0.0164
	(0.0551)	(0.0598)	(0.0532)
Uninsured Rate	-0.0448***	-0.0367***	-0.0370***
	(0.00663)	(0.00734)	(0.00727)
Interaction	-0.00989***	-0.0101***	-0.0101***
	(0.00261)	(0.00354)	(0.00303)
Mean of dependent variable	1,345.04	1,345.04	1,345.04
Controls			
Population	Yes	Yes	Yes
Age and Demographics	No	Yes	Yes
Unemployment Rate	No	Yes	Yes
Other Pertinent Laws	No	No	Yes
N	864	864	864

Notes: State population weighted estimates. Models include year fixed effect and state fixed effect. Pertinent Laws include Naloxone Access Laws, Good Samaritan Laws and Prescription Drug Monitoring Programs. Standard errors in parentheses are clustered at the state level. * p<0.10, ** p<0.05, *** p<0.01

Table A6: Placebo Results

Dependent Variable:	% White	% Black	% Age 0-15	% Age 16-35	% Age 36-64	% Age 65+	Unemployment
Medicaid	0.00952	-0.00195	-0.00134	0.00132	0.0000559	-0.0000559	0.220
Expansion	(0.00626)	(0.00192)	(0.00109)	(0.00112)	(0.00139)	(0.00139)	(0.201)
Log Population	0.121**	0.0242*	0.0178	-0.00308	0.00773	-0.00773	0.766
	(0.0519)	(0.0131)	(0.0141)	(0.0141)	(0.0113)	(0.0113)	(2.423)
Unemployment	-0.00202	0.000114	-0.000502**	0.0000295	0.0000249	-0.0000249	
Rate	(0.00241)	(0.000566)	(0.000225)	(0.000257)	(0.000206)	(0.000206)	
% Age 0-15	0.0336	-0.0739		-0.659***	-0.721***	-0.279***	-20.50**
	(0.417)	(0.134)		(0.0581)	(0.0494)	(0.0494)	(9.968)
% Age 16-35	0.889**	0.235*	-0.681***		-0.678***	-0.322***	1.246
	(0.391)	(0.125)	(0.0550)		(0.0480)	(0.0480)	(10.95)
% Age 36-64	1.053**	0.123	-0.894***	-0.814***			1.262
	(0.493)	(0.114)	(0.0436)	(0.0542)			(10.48)
% Black	-1.323**		-0.0307	0.0945*	0.0413	-0.0413	1.939
	(0.518)		(0.0539)	(0.0531)	(0.0390)	(0.0390)	(9.501)
% White		-0.108***	0.00113	0.0290***	0.0287*	-0.0287*	-2.790
		(0.0290)	(0.0143)	(0.00994)	(0.0160)	(0.0160)	(2.933)
N	846	846	846	846	846	846	846

Notes: Population weighted OLS Results. Models include year fixed effect and state fixed effect. Standard errors in parentheses are clustered at the state level. * p<0.10, ** p<0.05, *** p<0.01

Table A7: Placebo 2 year Lead State Level, 1999-2016

	All Opioids	Heroin	Other Opioids	Methadone	Synthetic	Other Narcotics
Medicaid Expansion	-0.00862	-0.317**	-0.158	0.261***	0.254*	-0.231*
	(0.0747)	(0.159)	(0.107)	(0.0699)	(0.147)	(0.138)
2 Year Lead	0.0598	-0.0190	0.00644	0.231***	-0.0283	0.0290
	(0.0439)	(0.0844)	(0.0494)	(0.0541)	(0.0841)	(0.0891)
Controls:						
Population	Yes	Yes	Yes	Yes	Yes	Yes
Age and Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Unemployment Rate	Yes	Yes	Yes	Yes	Yes	Yes
Other Pertinent Laws	No	No	No	No	No	No
Mean of Dependent	819.74	201.86	363.43	140.14	136.49	112.89
N	846	846	846	846	846	846

Notes: State population weighted Poisson estimates. Models include year fixed effect and state fixed effect. Pertinent Laws include Naloxone Access Laws, Good Samaritan Laws and Prescription Drug Monitoring Programs. Standard errors in parentheses are clustered at the state level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table A8: Negative Binomial Results, State Level, 1999-2016

	All Opioids	Heroin	Other Opioids	Methadone	Synthetic	Other Narcotics
Medicaid Expansion	-0.0999	-0.517**	-0.164	0.227***	0.112	-0.304**
	(0.0918)	(0.219)	(0.165)	(0.0710)	(0.173)	(0.123)
Controls:						
Population	Yes	Yes	Yes	Yes	Yes	Yes
Age and Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Unemployment Rate	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Dependent	819.74	201.86	363.43	140.14	136.49	112.89
N	846	846	846	846	846	846

Notes: State population weighted estimates. Models include year fixed effect and state fixed effect. Standard errors in parentheses are clustered at the state level. * p<0.10, ** p<0.05, *** p<0.01

Table A9: Poisson DDD, County Level, 2005-2016

	All Opioids	Heroin	Other Opioids	Methadone	Synthetic Opioids	Other Narcotics
Medicaid Expansion	0.0969	-0.126	-0.0885*	0.123	0.816***	-0.0352
	(0.0773)	(0.0992)	-0.0527	(0.0913)	(0.265)	-0.141
Uninsured Rate	-0.0302***	-0.0192	-0.0282***	-0.0138	-0.0325	0.00172
	(0.00568)	(0.0142)	-0.00668	(0.00954)	(0.0276)	-0.0106
Interaction	-0.00568	-0.00650	0.00576*	0.00239	-0.0428**	-0.0213**
	(0.00404)	(0.0126)	-0.00342	(0.00608)	(0.0184)	-0.0105
Mean of dependent variable	74.26	22.39	28.09	10.01	10.87	10.81
Controls:						
Population	Yes	Yes	Yes	Yes	Yes	Yes
Age and Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Unemployment Rate	Yes	Yes	Yes	Yes	Yes	Yes
N	32,573	18,449	29,806	25,798	26,364	17,796

Notes: Unweighted estimates. Model includes year fixed effect and state fixed effect. Standard errors in parentheses are clustered at the state level. * p<0.10, ** p<0.05, *** p<0.01

Table A10: Comparing County and State Level 2005-2016

	Heroin	Heroin	Heroin	Methadone	Methadone	Methadone	Other Unspecified Narcotics	Other Unspecified Narcotics	Other Unspecified Narcotics
County Level Data									
Medicaid Expansion	-0.149	-0.140	-0.203	0.261***	0.178**	0.164**	-0.338**	-0.212	-0.229*
	(0.149)	(0.136)	(0.134)	(0.0874)	(0.0724)	(0.0727)	(0.155)	(0.148)	(0.125)
N	18,449	18,449	18,449	25,798	25,798	25,798	17,796	17,796	17,796
State Level Data									
Medicaid Expansion	-0.204	-0.0939	-0.123	0.234***	0.0859	0.0674	-0.223	-0.171	-0.190
	(0.135)	(0.107)	(0.104)	(0.0768)	(0.0697)	(0.0682)	(0.140)	(0.149)	(0.129)
N	564	564	564	564	564	564	564	564	564
Controls:									
Population	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age and Demographics	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Unemployment Rate	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Other Pertinent Laws	No	No	Yes	No	No	Yes	No	No	Yes

Notes: Unweighted Poisson estimates. County models include year fixed effect and county fixed effect. State level models include year fixed effect and state fixed effect. Pertinent Laws include Naloxone Access Laws, Good Samaritan Laws and Prescription Drug Monitoring Programs. Standard errors in parentheses are clustered at the state level. * p<0.10, ** p<0.05, *** p<0.01

Figure A1: California Methadone Deaths

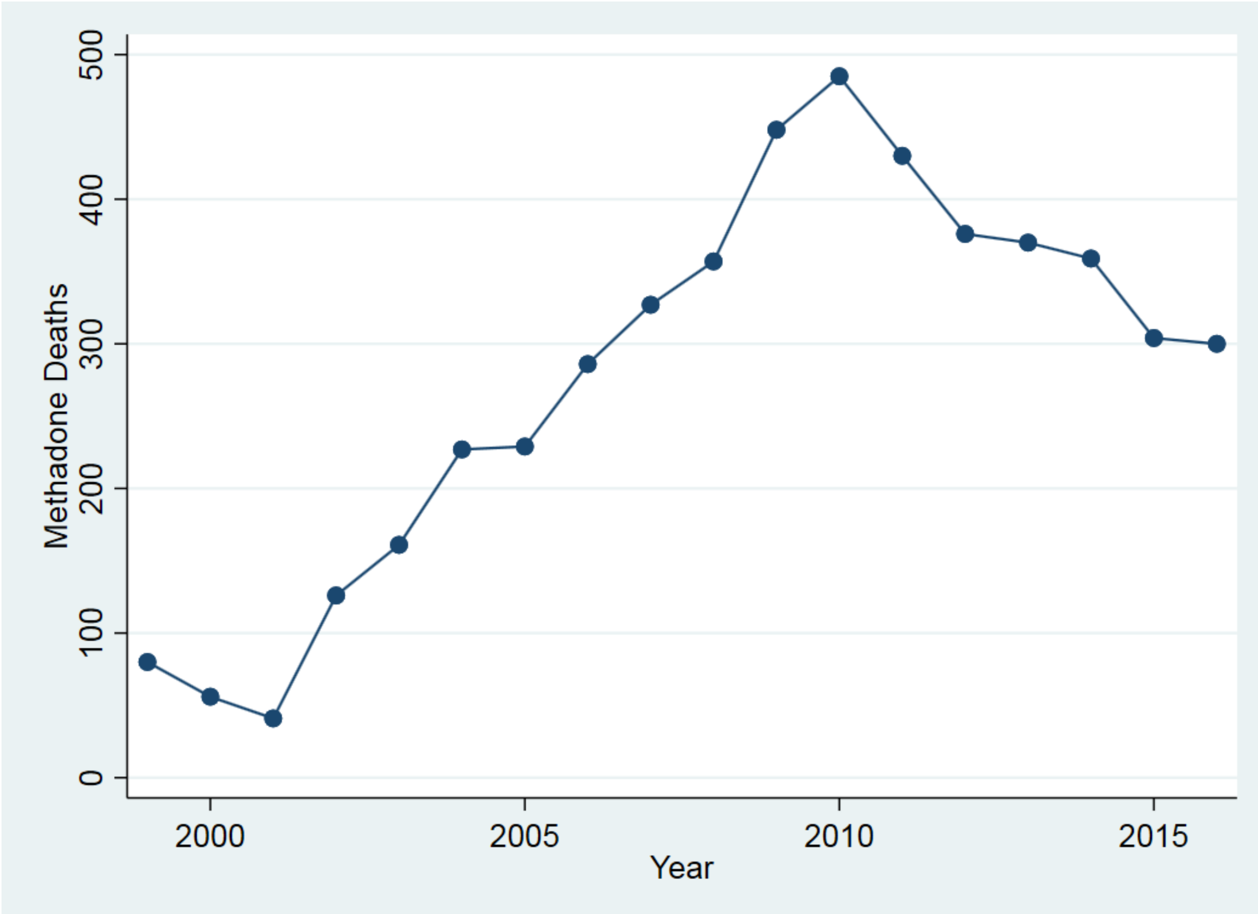
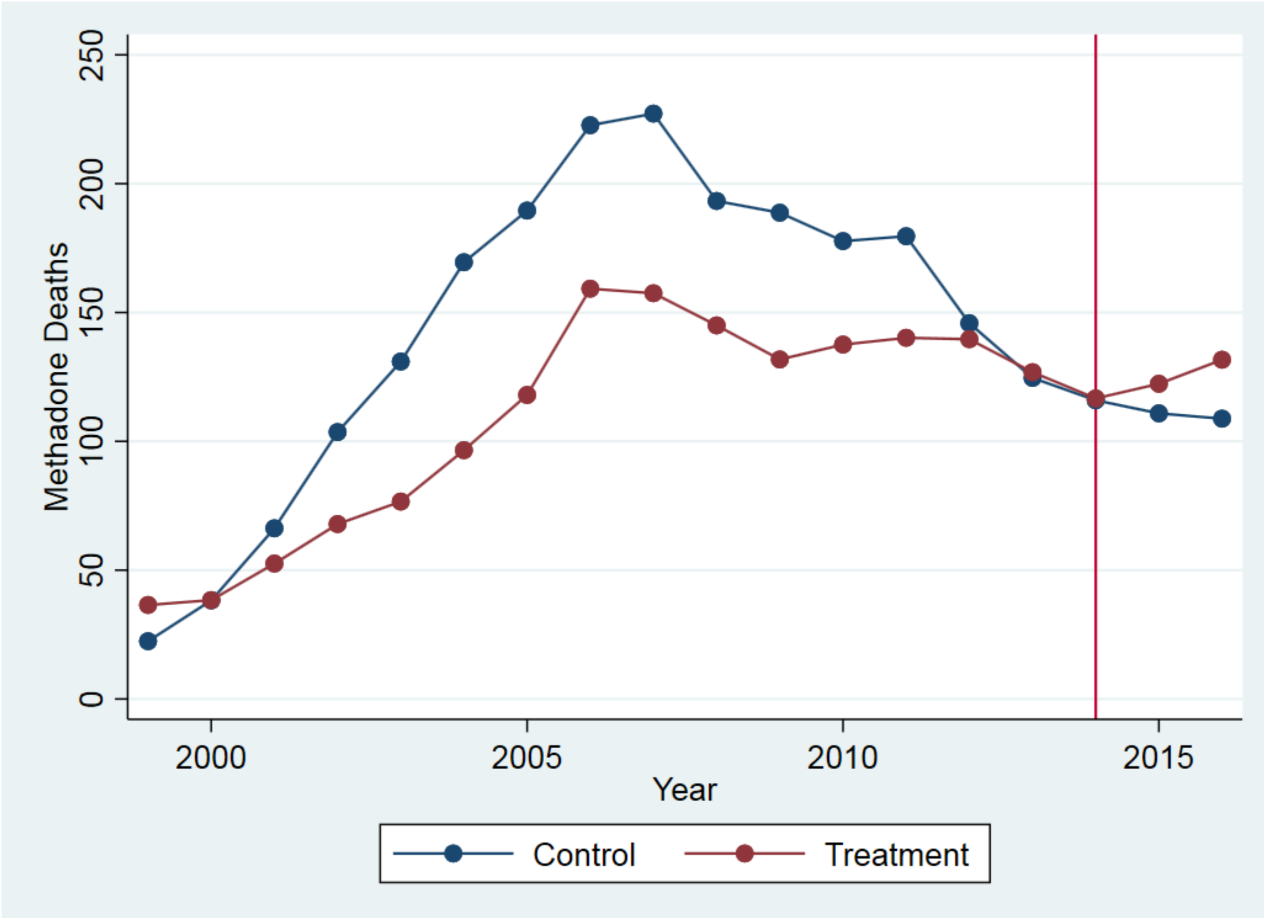


Figure A2: Methadone Population Weighted Means Plot



Notes: Treatment group includes only states that expanded Medicaid in 2014. Control group includes all non-expanding states. This plot exhibits the population weighted mean number of methadone deaths per state per year aggregated into treatment and control groups.