Effect of the ACA Medicaid Expansion on Prescription Opioid Utilization Patterns

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October 7, 2020

Abstract

Opioid abuse and opioid-related deaths have drawn serious public concern in the United States. There have been substantial efforts to manage opioid use by limiting opioid prescriptions. Along with the designated regulations, it is essential to understand other factors that could influence opioid use, especially those that have a larger scale. This paper studies the effect of the Affordable Care Act Medicaid expansion, one of the largest health insurance expansions in US history, on Medicaid prescription opioid utilization and reimbursements. I find that the Medicaid expansion is associated with an increase in total opioid prescriptions per population ages 19–64. However, the results suggest that post-expansion prescriptions are, on average, shorter or lower dose. Analyses of commonly misused opioids show that hydrocodone is the most affected substance, which makes up more than 50 percent of all opioid prescriptions. I do not find evidence that the Medicaid expansion is associated with the fentanyl epidemic.

Keywords: Affordable Care Act, health insurance, Medicaid, prescription opioid
JEL Codes: I12, I13, I18

*E-mail: anh.h.le@uky.edu. I thank my advisor, Charles Courtemanche, and my committee for their guidance. I am also grateful to participants at the Universiy of Kentucky seminars, the Kentucky Economic Association Annual Conference, the Indiana University Mini Health Conference, and the US Food and Drug Administration Research Seminar for their comments and feedback.

1 Introduction

Opioid abuse is a significant public health concern in the United States. According to the National Institute of Drug Abuse (NIDA), in 2018, 128 people in the United States died from an opioid overdose every day (NIDA, 2020). The epidemic started in the late 1990s with increasing prescription opioid overdose deaths and led to rapid increases in deaths involving heroin, starting 2010, and synthetic opioids, starting in 2013. This opioid crisis not only creates pressure on public health but also impacts social and economic welfare. Florence et al. (2016) estimate a cost of $78.5 billion for prescription opioid abuse in 2013, which includes healthcare, addiction treatment, productivity loss, and legal enforcement.

The medical use of prescription opioids as an analgesic for acute and post-surgical pain is not of serious concern. However, prolonged opioid use can lead to drug dependence and addiction. Moreover, the ready availability of prescription opioids is a primary factor leading to the initiation of non-medical use, and the risk of using prescription opioids for non-medical purposes is not limited to the individuals for whom the drugs are prescribed. More than 70 percent of non-medical opioid users obtained the drugs from a friend or relative (Jones et al., 2014; Lankenau et al., 2012). The Centers for Disease Control and Prevention (CDC) estimate that 40 percent of deaths from opioid overdose is related to a prescription opioid (CDC, 2020). Prescription opioids and non-prescription opioids, such as heroin, are pharmacologically similar, which suggests a higher probability of heroin initiation among prescription opioid users compared to non-users. There have been numerous studies regarding the relationship between prescription opioids and heroin consumption (Jones, 2013; Compton et al. 2016). Although most studies are descriptive, they find a consistent, positive association between the use of these two types of opioids. Jones (2013) finds that over 80 percent of heroin users used prescription opioids before trying heroin.

Since the rise of the opioid epidemic, there have been substantial efforts to manage prescription opioid use. Much attention has been paid to regulations and programs designed to control prescription opioid use, including prescription administering programs such as the state Prescription Drug Monitoring Programs (PDMPs), pain management clinic laws, and supply-side strategies such as adding abuse-deterrent controlled-release properties to drug formulas (e.g., OxyContin and Butrans). Health insurance coverage is another important channel that could affect prescription opioid use. The literature has long shown that health insurance increases the use of health services (Currie & Gruber, 1996a & b; Card, Dobkin, & Maestas, 2008) and prescription drugs (Duggan & Morton, 2010; Ketcham & Simon, 2008; Lichtenberg & Sun, 2007).

This paper starts by studying the link between an increase in health insurance access through the Affordable Care Act (ACA) Medicaid expansion and prescription opioid utilization. The ACA's implementation is an appropriate opportunity to study prescription opioid use for many reasons. First, the ACA has been the largest-scale health care reform in the United States since the introduction of Medicaid and Medicare in the 1960s. Since its implementation, the United States has experienced a nationwide increase in health insurance coverage. Studies that focus on the earlier years after the ACA find consistent increases in health insurance coverage in both Medicaid–expansion and non–Medicaid–expansion states. Second, there is a variation in states' decisions to expand Medicaid under the ACA. Initially, the Medicaid expansion was intended to occur nation-wide. However, a Supreme Court decision in 2012 allowed states to adopt the expansions optionally. At the time of the ACA's implementation (January 1, 2014), 25 states decided to expand Medicaid.

Empirically, assessing the relationship between health insurance and any type of health care utilization is challenging due to potential reverse causality, and prescription opioid use is no exception. On the one hand, having health insurance coverage increases access to opioid medication. On the other hand, individuals who demand prescription opioids are more likely to seek health insurance. The second empirical challenge that comes with estimating the effects of health insurance on prescription opioid use is omitted variable bias. Individuals with bad health are likely to have a higher demand for both health insurance and painkillers. The ACA's Medicaid expansion aims to target disadvantaged populations, which have less insurance coverage and, in general, have worse health. However, the fact that not every state adopted the Medicaid expansions provides plausibly exogenous variation in Medicaid eligibility for individuals in expansion and non-expansion states, which can mitigate the issues mentioned above.

This paper contributes to the existing literature in several ways. First, the paper provides a comprehensive analysis of the causal relationship between the Medicaid expansion, prescription opioid use (measured by per-population prescriptions and MMEs), and Medicaid spending. Research looking at the association between the Medicaid expansion and opioid prescriptions mainly focuses on per-enrollee prescriptions. However, it is necessary to investigate both measures, because changes in per-enrollee utilization could only capture the differences between the pre-expansion and post-expansion Medicaid populations, as the number of enrollees also increases in expansion states. Per-population estimates are more relevant when compared to total opioid prescriptions across all payers and other state programs.

Using combined data from the State Drug Utilization Data (SDUD) and the National Drug Code Directory, I employ a generalized difference-in-differences (GDD) framework to estimate the effects of the Medicaid expansion on prescription opioid use. The advantage of this strategy is that it can account for the variation in both states' decisions and time of expansion. Results show a positive effect of the Medicaid expansion on opioid prescriptions and MMEs per 1,000 adults under 65 and mixed results on Medicaid spending.

This paper also contributes by being the first to examine the heterogeneity among substances and to provide an implication of the Medicaid expansion's role in the on-going fentanyl and synthetic opioid epidemic. Identifying the changes among substances is important due to the fact that these substances differ in potencies and thus in prescribing patterns (i.e. strong opioids are not prescribed to opioid-naive patients). Moreover, opioid substances also differ in their mechanism of action, the way each substance interacts with opioid receptors, which can lead to discrepancies in their ability to induce addiction, as described by Stoeber et al. (2018). Thus, examining the heterogeneity among opioids can reveal if the change in utilization mainly reflects the change in the Medicaid-eligible population or if it suggests signs of opioid misuse.

I look at separate samples that contain all morphine, hydrocodone, oxycodone, and fentanyl prescriptions. Among these substances, hydrocodone is shown to have the largest increase in the number of prescriptions and MMEs. The results translate to about 32 prescriptions and 11,700 MMEs for every 1,000 people ages 19–64 (1.83 standard deviations). The effects on fentanyl, a highly potent synthetic opioid, are relatively small, about 1.6 prescriptions per 1,000 (0.5 standard deviations). These estimates also further suggest that the Medicaid expansion is not likely to have directly contributed to the fentanyl epidemic.

2 Background and Literature of the ACA

The ACA was implemented in 2014, with a goal to achieve nearly universal health insurance coverage in the United States. The ACA consists of three main parts that are commonly known as a "three-legged stool." The first leg consists of regulations that guarantee coverage for individuals. Insurance companies are required to base their premiums on community rating and issue coverage regardless of pre-existing health conditions. The second leg, or the individual mandate, includes regulations to prevent the potential death spiral[1] that the first component could cause. The third leg addresses concerns about affordability, which consists of subsidies and the Medicaid expansions. Individuals with incomes between 100 and 400 percent of the FPL, who are not eligible for Medicaid or employer-sponsored insurance, would qualify for premium subsidies. In addition to this nationwide subsidy program, states have the option to expand their Medicaid programs to individuals with incomes below 138 percent FPL at almost zero cost.[2]

2.1 Effects of the ACA Medicaid expansion on healthcare and health-related outcomes

Since the ACA's implementation, the literature on this healthcare reform has been rapidly growing among researchers and policymakers. Mazurenko et al. (2018), Antonisse et al. (2018), and Gruber & Sommers (2019) provide systematic reviews of the ACA-related studies. A large number of studies find that the ACA, especially the Medicaid expansion, is associated with an increase in health insurance coverage (Sommers et al., 2014; Sommers et al., 2015; Buchmueller et al., 2016; Wherry and Miller, 2016; Courtemanche et al., 2017-2019; Duggan, Goda, & Jackson, 2017; Frean et al., 2017; Kaestner et al., 2017).

There is mixed evidence of changes in health service utilization, including preventive care (Sabik, Tarazi & Bradley, 2015; Wherry and Miller, 2016; Simon, Soni, & Cawley, 2017; Courtemanche et al., 2017), hospital use (Akosa Antwi et al., 2015; Admon et al., 2019; Anderson et al., 2016), emergency services (Nikpay et al., 2017; Sabik et al., 2017; Pines et al., 2016; Courtemanche, Friedson, & Rees, 2019). There are also a vast number of studies investigating the association between the Medicaid expansion and specialized services (Singhal et al., 2017; Soni et al., 2018).

Studies exploring the link between the components of the ACA and prescription drug use document a general increase. Ghosh, Simon, & Sommers (2019) and Mahendraratnam et al.

[1] When premiums are based on community rating, people with worse health conditions are more likely to sign up than healthy people. As a result, premiums would eventually rise, which would further discourage healthy people to sign up, and so on.
[2] To learn more about the institutional details of the ACA, see Courtemanche et al. (2017) and Frean et al. (2017).

(2017) find that after the Medicaid expansion, aggregate prescription drug use increased about 17–19 percent. Mahendraratnam et al. (2017) also find that after one year of the expansion, Medicaid spending increased more than one-third in expansion states. Amuedo-Dorantes & Yaya (2016) also find an increase in prescription drug access due to the ACA's expansion of dependent coverage.

Higher utilization, however, does not necessarily translate to better health. Studies that examine the impact of the ACA on self-assessed health find mixed results. While a number of studies document improved self-reported health (Sommers et al., 2015; Sommers et al., 2016; Simon et al., 2017; Cawley et al., 2018), other papers find mixed results and insignificant changes in health measures (Courtemanche et al., 2018; Wherry and Miller, 2016). Most studies do not find an association between the ACA and risky behaviors or the use of risky-behavior-related products, including alcohol and tobacco (Courtemanche et al., 2018 & 2019; Cawley et al., 2018; Cotti et al., 2019). However, Maclean et al. (2019) find evidence that the Medicaid expansions provide higher access to smoking cessation medications.

2.2 The role of health insurance in the opioid epidemic

The association between health insurance and opioid analgesic use also poses an important question yet has not been fully understood. Having health coverage provides individuals with acute pain issues, such as post-surgical pain and late-stage cancer pain, with the necessary pain relievers. However, having access to opioid analgesics at a lower cost can lead to moral hazard among individuals who do not need such medication. An increase in demand for opioids can also lead to spillovers. Powell et al. (2020) examine the impact of Medicare Part D on opioid supply and find an increase in opioid abuse treatment admissions and opioid-related mortality among the Medicare-ineligible population. Soni (2018) documents a substitution effect between over-the-counter pain relievers and prescription pain relievers among the Medicare-eligible population. The structure of a health insurance program could also affect opioid analgesic utilization. Baker et al. (2018) find that enrollment in Medicare Advantage reduces the likelihood that beneficiaries fill an opioid prescription.

Several studies focus on the impact of ACA Medicaid expansion on opioid-related outcomes. The current literature focuses on the two channels by which the Medicaid expansion can affect the opioid epidemic. The first channel relies on the theory that, by increasing access to drug-dependence and opioid-addiction treatments to the target population, the

Medicaid expansion could lower the number of opioid-dependent individuals and reduce opioid-involved deaths. Most studies in this area find that the Medicaid expansion is associated with higher utilization of treatment services and admissions for opioid use disorder (Wen et al., 2017; McKenna, 2017; Andrews et al., 2018; Meinhofer & Witman, 2018; Sharp et al., 2018; McCarty et al., 2019; Maclean & Saloner, 2019). Meinhofer & Witman (2018) also find no evidence that the increase in treatment admissions from Medicaid beneficiaries is crowding out of other types of health insurance. Feder et al. (2017), however, find no evidence of changes in treatment service use among people with heroin use disorder, despite higher coverage. Olfson et al. (2018) find no changes in treatment service use among the low-income population.

The second channel focuses on the fact that Medicaid has increased access to care. Given that the eligible population is less healthy and more prone to conditions that require analgesic medications, the Medicaid expansion could be efficient in serving the target population. However, opioid analgesics can initiate addiction and abusive behaviors among prescribed and non-prescribed users. Results have been mixed among these studies. Sharp et al. (2018) find a negative but statistically insignificant association between the Medicaid expansion and per-enrollee number of prescriptions, while Cher et al. (2019) find a positive but insignificant impact on the same measure. Saloner et al. (2018) also find an increase in the number of opioid prescriptions paid by Medicaid, using data from California, Maryland, Washington, Florida, and Georgia. Given that the two channels discussed above could happen concurrently and create opposite effects on the level of opioid usage, estimates of the association between the ACA and opioid use represent the net effect of the two channels.

Studies that investigate the effects of the Medicaid expansion on opioid-related fatalities also find mixed results. McInerney (2017) and Kravitz-Wirtz et al. (2020) find a reduction in opioid-related deaths and death rates associated with the Medicaid expansion. However, the association between the Medicaid expansion and opioid-related deaths is unclear, according to Abouk et al. (2019) and Averett, Smith, & Wang (2019). The mixed results and the dynamic nature of opioid-related issues necessitate a thorough analysis of the utilization patterns of prescription opioids under the Medicaid expansion.

3 Data

3.1 Measuring Medicaid opioid utilization

The main data come from the State Drug Utilization Data (SDUD) collected by the Centers for Medicare and Medicaid Services (CMS). Since the start of the Medicaid Drug Rebate Program (MDRP) in 1991, the CMS has required states to submit records of Medicaid prescription drug utilization. Under the MDRP, participating drug manufacturers are required to provide rebates to the states and the federal government in exchange for coverage by Medicaid. The SDUD records quarterly information of state-reported prescription drugs that are reimbursed by Medicaid, including the number of prescriptions and total reimbursements by covered National Drug Code (NDC). Reimbursement data contain the amounts that Medicaid paid to providers, which does not account for manufacturer rebates.[3] The data used in this paper span the years 2011–2017.

I do not include data prior to 2011 for two reasons. First, the ACA Young Adult Coverage extension implemented in 2010 has been shown to have impacted opioid-related outcomes among the population ages 18–25 (Wettstein, 2019). Excluding data from 2010 and earlier could avoid capturing the short-term shocks in prescription opioid use that could have come from this extension. Second, it was not until the enactment of the ACA in March 2010 that the CMS required states to report prescriptions for Medicaid patients who are enrolled through managed care organizations (MCO). Prior to this time, drug manufacturers were only obligated to provide rebates to states for prescriptions that were purchased through the fee-for-service (FFS) scheme. Missing data of MCO prescriptions in 2010 and earlier could be an estimation threat because states are differential in terms of FFS – MCO structure. Without utilization from MCOs, reported data would incorrectly present the actual number of Medicaid prescriptions in each state and create bias.

To compile utilization data for prescription opioids, I create a list of prescription opioid NDCs by matching brand-name and generic opioid drug names with all corresponding NDCs from the FDA's National Drug Code Directory. To account for new drugs that enter the CMS system, I match the drug names with the Medicaid Opioid Drug lists provided by the CMS. [4] The goal is to include all opioid substances and avoid the potential bias coming from the

[3]The SDUD does not include drugs from state-only programs and other federal programs such as the 340B Drug Pricing Program.

[4]https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/Medicare-

heterogeneity across substances. Table 8 presents a list of common prescription opioids. Next, the opioid NDCs are linked to the SDUD to create a Medicaid utilization dataset for opioid prescriptions only. I exclude medications that are commonly prescribed for addiction treatments such as buprenorphine, naltrexone, and naloxone. Data are aggregated by state and year. The SDUD has two limitations. First, NDCs with fewer than 11 prescriptions in a state-quarter cell are suppressed. Second, the reported quarter may represent the time the NDC was dispensed or paid by the state rather than the time of actual utilization. Aggregating utilization by year could lessen the effect of these measurement errors.

For each outcome category of Medicaid opioid utilization (number of prescriptions and Medicaid reimbursements), I construct two measures: per 19–64 population, and per-enrollee using state population data from the US Census Bureau and Medicaid enrollment data from the CMS Medicaid Budget and Expenditure System (MBES) and the Henry J. Kaiser Family Foundation (KFF).[5] Data on Medicaid reimbursements are adjusted to 2011 dollars.

3.2 Treatment Variable

States receive a treatment status from the year that they implemented a Medicaid expansion, either through the ACA or through their own programs. Accordingly, treatment states can be divided into three groups. The first group consists of states that expanded in 01/2014 and did not have prior expansions. The second group consists of states that expanded Medicaid prior to 2014, under Section 1115 waivers (California, Connecticut, Delaware, DC, Minnesota, New Jersey, and Washington) and/or had their own expansions with similar criteria to the ACA Medicaid expansions (Delaware, Massachusetts, New York, Vermont, and DC). These states are defined to have a treatment status before 2014. States that already have similar criteria to the ACA Medicaid expansions are considered "early" expansion states. The third group consists of states that expanded after 01/01/2014. These states are Alaska, Indiana, Louisiana, Michigan, Montana, New Hampshire, Pennsylvania, Virginia, Maine, Idaho, Utah, and Nebraska.[6] As the time of this paper, 37 states including DC have adopted the expansion (KFF 2020).[7]

Provider-Charge-Data/OpioidMap_Medicaid_State

[5]The MBES did not start reporting Medicaid enrollment data until January 2014.

[6]See table 1 for specific years.

[7]States expanded after 2017, Virginia, Maine, Idaho, Utah, and Nebraska, are treated as non-expansion states in this paper.

3.3 Control Variables

Numerous factors can affect prescription opioid use. Therefore, when estimating the effects of the Medicaid expansion on prescription opioids, it is crucial to account for potential confounders that can affect state-level opioid utilization. The paper's main model includes two sets of controls. The first set includes variables that control for state demographic characteristics (such as the share of individuals that is white and the share of the female population), using data from the ACS, and economic conditions, including state poverty rate of the population ages 19–64 (KFF), unemployment rate, and minimum wage (UKCPR Welfare Data).

The second set of covariates controls for major state prescription opioid regulations. Since the rise of opioid use, there has been substantial public effort to control the epidemic. State opioid policies have been shown to have some impact on prescription opioid use, which can create bias in the estimates if they are correlated with these states' decision to expand Medicaid. I include an indicator for states' adaptation of the Prescription Drug Monitoring Programs-mandate (PDMP-mandate)[8] collected from the Prescription Drug Abuse Policy System (PDAPS). Although state PDMP consist of multiple components, the PDMP-mandate has been shown to impact prescription opioid use, compared to other parts of the regulation (Wen et al., 2017).[9] Other regulations include the Pain Management Clinic Laws[10] and the Prescription Drug Time and Dosage Limit Laws. Data on states' implementation of these programs are collected from the PDMP Training and Technical Assistant Center. I also include state recreational marijuana law status, following Meinhofer and Witman (2018). Table 7 reports the effective time of these regulations.

4 Methodology

The empirical strategy of this paper aims to identify the effect of the Medicaid expansions on Medicaid utilization and reimbursements. The variation in states' decisions to expand Medicaid provides a natural identification for a difference-in-differences (DD) design. However, not all states that expanded Medicaid did so in January 2014. Previous literature has

[8]PDMP are state-implemented programs that record patients' prescription history to monitor potential fraudulent behaviors such as "doctor shopping," a behavior marked when a patient obtains prescriptions from five or more prescribers (Buchmueller and Carey, 2018).

[9]A state is defined as having the PDMP-mandate when it requires a healthcare professional to check with the system before prescribing or dispensing opioids.

[10]Pain clinic laws refer to regulations on pain management clinics such as facility and staffing certification or supply limit regulations (PDAPS.org).

taken this variation into account in many ways, including dropping the early expansion states or assuming that the impact coming from these states is negligible. To both estimate the effects coming from the early and late expansion states and maintain the sample size, in the baseline model, I follow a generalized difference-in-differences framework described in equation (1). I later include estimation results of the main model but exclude states with their own pre-ACA expansions as a robustness check.

$$Y_{st} = \alpha + \beta Medicaid_{st} + \gamma X_{st} + \delta P_{st} + \eta_s + \lambda_t + \varepsilon_{st} \tag{1}$$

The outcome variable of interest, Y_{st}, is a measure of Medicaid prescription opioid utilization or reimbursement in state s and year t. $Medicaid_{st}$ is the treatment indicator, which equals 1 if period t is the year state s expanded Medicaid and after. X_{st} is a vector of covariates that control for time-varying state-specific demographic and economic conditions that could have influenced both state opioid utilization and the decision to expand Medicaid, which is described in more details in section 5.1. P_{st} is a vector of opioid-related policies described in Section 2.3. The model also includes state and year fixed effects, η_s and λ_t, to account for heterogeneity across states and year-specific unobservables, respectively, and ε_{ist} is the error term. All specifications are weighted by state population ages 19–64. I also include results from unweighted regressions in the robustness check section.

The coefficient of interest, β, measures the differential change in Medicaid opioid utilization or reimbursements between control and treatment states. From the previous literature, the ACA's implementation results in higher health coverage and higher utilization. Thus, it is natural to expect β to be positive. However, there is also evidence that the ACA increases opioid treatment admissions and medication. If additional access to opioid treatment decreases opioid use more extensively than the increase from more coverage, β could also be negative or zero.

5 Results

5.1 Summary Statistics

Table 2 presents the summary statistics in 2013, the pre-treatment period for most states. The average per population (in thousands) opioid utilization in a state is about 122 prescriptions, which corresponds with an average of approximately $4,800 in Medicaid spending and over 111,000 MMEs. Oxycodone accounts for the largest share: about 30 percent of all opioid prescriptions. Before the ACA, the average uninsured rate was approximately 20 percent. On average, demographic characteristics were similar between the control and treatment states. However, economic and political characteristics were different between the two groups. Medicaid expansion states have a higher minimum wage but also a higher unemployment rate. Sixty percent of house and senate seats in expansion states are Democratic, compared to about 33 percent in non-expansion states. Expansion states also differ from non-expansion states in terms of opioid policies. For example, by 2013, 24 percent of expansion states implemented the PDMP-mandate, compared to 8 percent of the non-expansion states.

Figures 1 and 2 show total opioid prescriptions (per 1,000 people ages 19–64) by state in 2013 and 2014, respectively. For ease of comparison, the scale for figure 2 is kept similar to figure 1. Between the two years, prescription rates increased in most states, including states that did not expand in 2014. To further access the trends between expansion and non-expansion states, figures 3a and 3b present the average opioid utilization and reimbursement rate (per 1,000 people ages 19–64) in expansion and non-expansion states. The SDUD provides utilization data at the end of each period; therefore, the time of the expansion (January 1, 2014) corresponds with the year 2013 on the graphs, instead of 2014. The data show a slightly increasing pre-trend in both expansion and non-expansion states (figure 3a.) After the ACA's implementation, there is a sharp increase in the overall trend, but Medicaid expansion states experience a larger change. The fact that there is an increase in utilization even in non-expansion states can be potentially explained by the ”welcome mat” effect, or the ”woodwork effect,” described in Frean et al. (2017).[11] The pre-trends of Medicaid spending in figure 3b, on the other hand, do not look similar. However, the graphs present the time series trends rather than the identification assumption that the model relies on, which are conditional on the covariates. I later examine the trends using an event study design and control for pre-trends in a robustness check.

It is also noticeable that the trends of prescriptions and reimbursement amounts do not

[11] The Medicaid expansion can affect both Medicaid newly- and previously-eligible individuals. For individuals that are eligible for Medicaid coverage before the expansion, there are no official changes to their eligibility for Medicaid after 2014. However, a large-scale health care reform such as the ACA can increase awareness among eligible non-enrollees. Also, there will be a reduction in social stigma with receiving Medicaid because the expansion increases income eligibility (in most states) and the Medicaid population. For this reason, the ”welcome-mat” effects are present in both expansion and non-expansion states.

move in tandem, which suggests that underlying factors that influence Medicaid spending can be different from those affecting the number of opioid prescriptions. These discrepancies are not unexpected because, although Medicaid reimbursements are calculated by average wholesale price rather than retail price, there is evidence that manufacturers could respond to policies (Dranove et. al, 2017). Moreover, drug prices can change from new drug entrance, including generic drugs.

Opioid prescriptions and reimbursement seem to peak in 2015 and start to decrease in 2016 and 2017. These changes could reflect a nationwide awareness and effort to manage prescription opioid use. Another possible explanation is that in July 2016, the Comprehensive Addiction and Recovery Act (CARA) was signed into law. This is the most comprehensive addiction policy in the US within 40 years.[12] Its main goal is to increase prevention and recovery support to localities, especially areas that are more affected by addiction issues. Along with other concurring state and local policies, the CARA might have played a role in the downward trend of opioid prescriptions.

5.2 Total opioid utilization

Table 3 - panel A presents the estimates of the effects of the Medicaid expansion on prescription opioid utilization from the baseline model. Measures of the dependent variable include number of prescriptions per population age 19–64 and per enrollee (both in thousands). All regressions are weighted by state population age 19–64 and the standard errors are adjusted for heteroskedasticity and clustered by state. All specifications observe a positive and statistically significant association between the Medicaid expansion and opioid use. Column 1 reports estimates of the naïve specification, including state and year fixed effects only. Column 2 includes state economic and demographic controls. The preferred specification is reported in Column 3, which includes state characteristics and opioid-related policy variables. The estimates do not seem to have drastic changes across specifications. However, including state characteristics and opioid-related policies seems to slightly increase the magnitude and precision of the estimates. Results from the preferred specification show an increase of 60.3 prescriptions per 1,000 people and 77.5 prescriptions per 1,000 enrollees when states expand Medicaid, about 49.5 percent and 17.1 percent from the 2013 full sample means, respectively.

Table 3 - panel B presents the results for Medicaid reimbursements. There is evidence

[12]For further details of the CARA, see https://www.congress.gov/bill/114th-congress/senate-bill/524

that Medicaid spending also increases due to the expansion. Spending per 1,000 people (age 19–64) increases by $973.5, which is 20.37 percent of the 2013 full-sample mean. However, estimates for spending per 1,000 enrollees become small and statistically insignificant. One potential explanation is that prescriptions for newly enrolled beneficiaries contain lower dosages compared to existing beneficiaries. Scaling the estimates by the number of enrollees would decrease the magnitude. Another explanation is that there are other mechanisms from the Medicaid expansion, aside from prescription utilization, that could influence reimbursement amounts, such as manufacturer response and managed care organizations (MCOs). In one of the robustness analyses, I control for the ratio of prescriptions administered by MCOs to evaluate the extent to which MCOs could influence opioid use and spending.

6 Extended measures of opioid use

6.1 Morphine Milligram Equivalent Units

Next, I examine the results accounting for substance strength. Specifically, I calculate a new outcome variable that measures potency in "units," using the CDC's guide to obtain the "opioid oral morphine milligram equivalent conversion factors," or MME factors. The formula is described in equation (2).

$$MMEs = drug\ strength \times MME\ factors \times total\ units \tag{2}$$

where *MMEs* stands for morphine milligram equivalent units, *drug strength* is the unit strength of the substance associated with each NDC, *total units* is the number of units reimbursed through Medicaid. MMEs measure total morphine milligram equivalent units of opioid reimbursed by Medicaid. Ideally, researchers would also wish to observe daily dosage,[13] but due to data limitations, I could only calculate potency based on substances and the number of reimbursed units. However, looking at opioid use using MMEs is important for two reasons. First, opioids (both prescription and illicit) differ not only by strength but also by substance. Higher-dosage and higher-potency substances increase the risk of addiction and overdose. Thus, it is useful to also understand the amount of opioid used in addition to the number of prescriptions. Second, if the change in the number of prescriptions is dispropor-

[13]Daily dosage is measure by MMEs divided by the number of days prescribed.

tionately distributed among lower-dosage prescriptions, the effect on prescriptions will be higher than the effects on potency units.

Table 3 - panel C presents the results of re-estimating the baseline model using the number of reimbursed MMEs as an outcome variable. The Medicaid expansion is associated with higher MMEs prescribed per 1,000 people. The preferred estimate in column 3 shows an increase of 26,070 MMEs when states expand Medicaid.[14] When weighting the number of MMEs by the number of beneficiaries, similar to the results for Medicaid spending, the coefficients become small and indistinguishable from zero. Again, if new enrollees are prescribed with less potent substances and/or for shorter periods, per-enrollee measures will become smaller than per-population measures. I explore this possibility in the next section.

6.2 Effects of the Medicaid expansion by common opioids

Opioid potency also varies across substances. Certain drugs are more often involved in opioid abuse and death incidents than others. Among all prescription opioids, hydrocodone, oxycodone, morphine, and fentanyl are related to the most overdose deaths and abuse. According to the morphine milligram equivalent factor scale, morphine and hydrocodone are equally potent, with MME factors of 1; oxycodone has an MME factor of 1.5; and fentanyl has MME factors ranging from 0.13 to 7.2, depending on the form.[15] Fentanyl is an important substance to investigate due to not only its potency[16] but also the severe impact of illegal fentanyl starting in 2013.[17] Prescribed fentanyl can take the form of tablets/lozenges, liquid (oral or nasal spray), injections, and transdermal patches. The most commonly prescribed forms are transdermal patches (52.82%) and injections (47.15%). Injectible fentanyl, however, is more common in inpatient settings and is excluded in some analyses. Fentanyl patches, especially in extended-release forms, can be dangerous if misused due to the high concentration. Although up to the time of this paper, most fentanyl-related incidents involve illicit fentanyl rather than prescription fentanyl, it is still critical to answer the question of whether the Medicaid expansion is associated with the fentanyl epidemic through prescription fentanyl.

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[14] Because the data does not contain prescription lengths, it is not possible to compare the estimates to a typical or unusual opioid dose.

[15] Fentanyl is measured in mcg, while others are measured in mg.

[16] Fentanyl is 50 to 100 times more potent than morphine (CDC 2020).

[17] From 2013 to 2017, the number of overdose deaths that involved fentanyl has increased the sharpest, compared to other opioids. In 2017, fentanyl accounted for 30,000 of 72,000 overdose deaths (NIDA, 2018), although most fentanyl-related deaths come from "street" fentanyl rather than prescription fentanyl.

There also has been some evidence that oxycodone has a higher misuse tendency compared to morphine and hydrocodone (Wightman et al., 2012). Accessing the heterogeneity in utilization among these drugs is relevant since the results can inform policymakers about areas that need more attention. To examine the heterogeneity, I re-estimate equation (1) separately, allowing the outcome variables to be measures of each drug above. Each drug category includes utilization data for both the corresponding brand-names and generics. Figures 4 to 7 (both a & b) present trends in the number of prescriptions and Medicaid reimbursements by commonly misused opioids. Similar to figure 3, prescription utilization pre-trends of the treatment and control groups for each opioid are parallel. However, except for hydrocodone, trends in Medicaid spending mostly differ between the two groups.

Table 4 reports the estimates of commonly misused substances. Panel A presents the results of per-population measures, and panel B presents per-enrollee results. Columns (1) to (4) contain estimates for samples that include only prescriptions of morphine, hydrocodone, oxycodone, and fentanyl. Column (5) lists results for other opioids for comparison. The effects of the Medicaid expansion vary across substances. In panel A, hydrocodone observes the largest impact, with an increase of 32 prescriptions per 1,000 people, which is almost 1.5 times the 2013 mean. The effects on oxycodone and fentanyl are both positive, but are smaller, about 36 percent of the baseline mean. There is no significant impact on morphine prescriptions. In terms of Medicaid spending and MMEs, the impact remains largest for hydrocodone. Compared to other substances, hydrocodone has a lower potency (MME factor = 1) and is usually prescribed in lower doses. Therefore, hydrocodone is more common among patients (Jeffery et al., 2018). Furthermore, results for hydrocodone continue to be positive among per-enrollee measures, while estimates for other substances become smaller and statistically insignificant (panel B), although oxycodone takes the largest share of all opioids in 2013.

Although there is a small increase in the number of fentanyl prescriptions, the estimates are not significantly different from zero in other measures. Fentanyl is usually prescribed to patients with acute pain problems such as from surgeries and cancer, which are not likely to have large responses to the Medicaid expansion given that the new enrollees are, on average, healthier than the former Medicaid population. In other words, there is no evidence that the Medicaid expansion is associated with the increase in fentanyl-related overdose deaths through prescription fentanyl.

7 Event-Study Model

For the parameter β in equation (1) to be valid, changes in prescription opioid utilization through Medicaid are assumed to be similar in the treatment and control groups in the absence of the Medicaid expansion, conditional on the observables. This assumption can be violated if there are unobservables that influence the supply and demand for prescription opioids yet correlate with the ACA Medicaid expansion. Figures 3–7 show some cases where the pre-trends in Medicaid reimbursement are not similar between the control and treatment groups. However, it is necessary to examine the identifying assumption conditioning on the covariates. I employ a flexible event-study framework, which brings two advantages. First, it can assess pre-trends while allowing the time of treatment to vary by state. Second, the model can investigate the overall dynamic impacts after the expansions. This is useful because there has recently been evidence of a gradual impact of the ACA on health-related outcomes (Courtemanche et al., 2019). The event study model is described in equation (3):

$$\begin{aligned} Y_{st} = \alpha + \sum_{\tau=-2,\tau\neq-1}^{2} \beta_\tau(Medicaid_{s\tau}) + \beta_{-3}Medicaid_{-6to-3} + \beta_3 Medicaid_{3to6} + \gamma X_{st} \\ + \delta P_{st} + \eta_s + \lambda_t + \varepsilon_{st} \end{aligned} \tag{3}$$

where Y_{st} is an outcome of opioid utilization. β_τ parameters measure the effect of the Medicaid expansions on state s prescription opioid use if year t is τ years after state s expanded Medicaid. β_{-3} and β_3 are indicators if year t is three to six years before and three to six years after state s expanded Medicaid, respectively. Because most expansion states adopted the expansion in 2014, I group the further periods to minimize state compositional effects from the early and late expansion states. The other terms, X_{st}, P_{st}, η_s, λ_t, and ε_{st}, are defined as in equation (1). Under the parallel trend assumption, β_k (for all $k < 0$) would equal zero. In other words, the test for pre-treatment trends is equivalent to the t-test that β_{-3} to β_{-2} equal zero. I omit the year before state s expanded Medicaid ($\tau = -1$) as the reference year.

Figures 8 to 10 present the event study results for different utilization measures of the dependent variables: per 1,000 people (age 19–64) and per 1,000 enrollees. All of the estimated coefficients associated with pre-treatment years are not statistically different from zero. The test of joint significance, where the null hypothesis is $\hat{\beta}_{-3}$ equals $\hat{\beta}_{-2}$ and zero, also fails to reject the null hypothesis. These results indicate that conditional on the covariates, the parallel-trend assumption is not violated, even if the visual evidence does not show identical pre-trends. After the expansion, there are continued effects of the Medicaid expansions on per-population prescriptions. Total opioid utilization observes a steadily positive and significant impact every year for $t > 0$. The results for Medicaid spending and total MMEs, however, are smaller and less precise. Figures 11 to 14 present the event-study results that assess the parallel trend assumption for individual substances.

8 Robustness Checks

In this section, I examine the sensitivity of results from the baseline model. The robustness checks fall into two main categories: (1) changes in the covariates that account for potential policy- and market-related confounding factors and (2) changes in the model specifications.

Table 5 reports the estimates from group (1) sensitivity checks. I first consider a channel of the ACA that could potentially influence Medicaid prescription drug utilization. Dranove et. al (2017) find evidence of a reduction in Medicaid spending as states increase the share of drug benefit administered by MCOs, which happens partly as a response to the change in the ACA's manufacturer rebate rule. Therefore, MCOs may play a role in opioid prescribing and spending patterns. To account for changes in MCO penetration, I construct a variable that equals the number of prescriptions utilized through MCOs divided by the total number of prescriptions for each state-year pair. States' political characteristics are also potential confounders. It is widely known that blue states are more likely to expand Medicaid compared to red states. To the extent that state pollical characteristics could influence opioid use, I include the shares of state house and senate that are Democratic obtained from the UKCPR Welfare Data.[18] DC and Nebraska were excluded from this specification because they are unicameral.

Population composition might also affect prescription opioid use if (1) the newly eligible population in expansion states systematically has a higher demand for prescription opioids due to age composition or (2) individuals who are in higher need of opioid medications and eligible for Medicaid coverage but not living in an expansion state migrate to such states for coverage. These mechanisms, if true, could create an upward bias to the estimates. To account for population composition, I control for states' share of population ages 26–54, the age group that is most affected by the Medicaid expansion. The results are reported in

[18]Other political variables were excluded due to lack of variation.

table 5, column (3). Similar to columns (1) and (2), the estimates are robust to these changes, which suggests that composition is not driving the results. In another sensitivity check that accounts for migration, I re-estimate equation (1), using population shares of individuals ages 19–64 as a dependent variable. The results suggest that migration and changes in population composition are not driven by the Medicaid expansion, conditional on the covariates.[19]

In the next part, I consider the sensitivity of the estimates to the model itself. First, I include interaction terms of US Census Division and year indicators to further control for trends in existing regional-specific characteristics, such as opioid-related (both legal and illegal) or economic conditions, that might have influenced Medicaid utilization. Results are shown in table 6, column 1. Column 2 reports the results from the sample that excludes states with their own pre-ACA Medicaid expansions. The estimates from both specifications are smaller in magnitude than the main estimates. However, the changes are small, and the sign and significance remain similar in most cases. One exception is that the effects on per-population reimbursements (reported in panel A) become statistically insignificant. I present the results when re-estimating equation (1) without weighting in column (3) as a reference. Last, column (4) reports the estimates when controlling for state-specific pre-trends. The estimates are quantitatively similar to those in Table 3 in most cases, with an exception of MMEs used per enrollee in Table 6 - Panel B, where the estimates are noisy and sensitive to different specifications due to large standard errors. However, there are no specific patterns across the specification.

9 Discussion and Conclusion

This paper investigates the effects of the Medicaid expansions on different measures of opioid analgesic utilization. The findings add to the understanding of the Medicaid expansion's role in the opioid epidemic and the ongoing discussion of the ACA repeal. In addition to studies presenting evidence that the Medicaid expansion is associated with higher substance use disorder treatment utilization, I find that the Medicaid expansion is also associated with an increase in opioid analgesic prescriptions. There is a consistently positive effect of the Medicaid expansion on per-population opioid prescriptions, with about a 50 percent increase in the number of opioid prescriptions per 1,000 people ages 19–64. Per-enrollee prescription

[19]Results are not reported for brevity.

use observes an increase of about 16 percent; however, in line with previous studies, the per-enrollee estimates are not as robust. These results suggest that the Medicaid expansion provides access to opioid painkillers to more people, but the post-expansion enrollees were not particularly utilizing more prescriptions.

Results on Medicaid spending and MMEs also follow a similar pattern, with evidence of higher per-population utilization but mixed results among per-enrollee estimates. The estimates show relatively larger changes in the number of prescriptions compared to Medicaid spending and MME outcomes, which suggests shorter or lower-dose prescriptions among the post-expansion Medicaid population. Separate analyses of individual substances reveal that the increase in prescriptions mostly comes from hydrocodone (more than 50 percent of all opioids), which is less potent and more common for shorter prescriptions, compared to other commonly prescribed opioids. Although the Medicaid expansion coincides with a sharp increase in fentanyl-related overdose deaths, this paper does not find evidence that the expansion is associated with the fentanyl epidemic through prescription fentanyl.

The findings can be evaluated in several layers. First, the Medicaid expansion provides health care coverage at almost zero cost to lower-income individuals, and it is well understood that low-income individuals are less healthy and are likely to have higher prescription drug utilization, including opioid analgesic use. In this sense, the expansion has served the target sub-population. The increase in utilization may also come from beneficiaries who had other types of health insurance before they were eligible for Medicaid, which represents a switch of payment sources for prescription opioids. Under this mechanism, the Medicaid expansion is less efficient in terms of serving the target population due to crowding out. However, Saloner et al. (2018) find that the crowding-out effects on opioid prescriptions filled by other payment sources (cash, private insurance, and Medicare) are relatively small and not statistically significant. Last, utilization could increase due to moral hazard. Although the results do not suggest an unusual utilization pattern, they are applied to shorter-term interpretations while addiction is also a long-term health concern. In general, greater access to opioids comes with the risks of addiction, overdosing, and possibly lead to increased addiction treatment utilization. These risks are not limited to prescribed users but also extended to non-prescribed users.

There are some limitations to this paper. First, the data measure utilization only, so I cannot control for beneficiaries' characteristics or explicitly identify whether a prescription is prescribed to a new patient or is a refill. The results, thus, do not distinguish between changes in the intensive and the extensive margin. Second, because the SDUD only contains Medicaid utilization data, the results are limited to the Medicaid population, which may not represent the effects of the ACA at the national level. Another limitation is that this paper does not account for the potential response from suppliers such as advertisements, physician incentives, and new drug entrance. The scope of this paper also does not cover potential spillover effects on non-opioid analgesic or illicit opioids. These points suggest the next natural questions for future studies that aim for a deeper understanding of the role of health insurance in the opioid epidemic.

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Figure 1: Medicaid opioid prescriptions per population (1,000s) ages 19–64: 2013

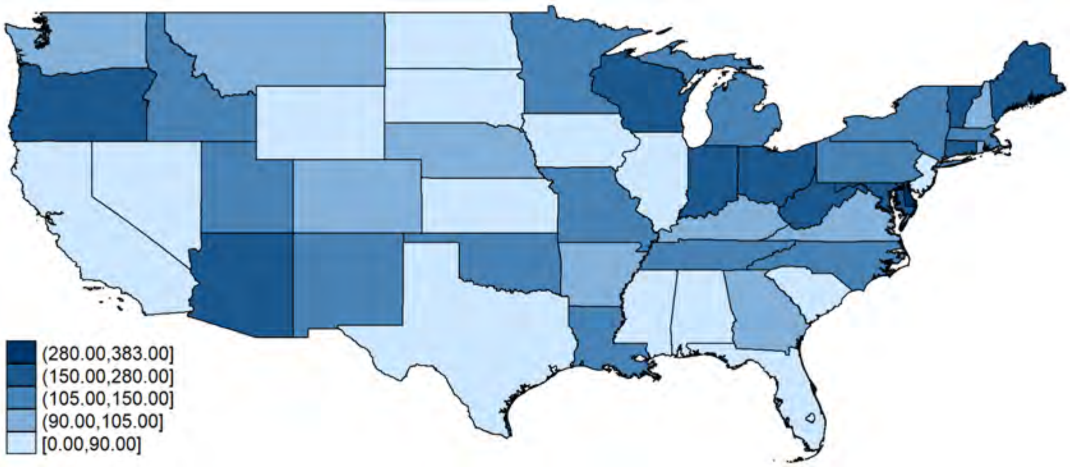


Figure 2: Medicaid opioid prescriptions per population (1,000s) ages 19–64: 2014

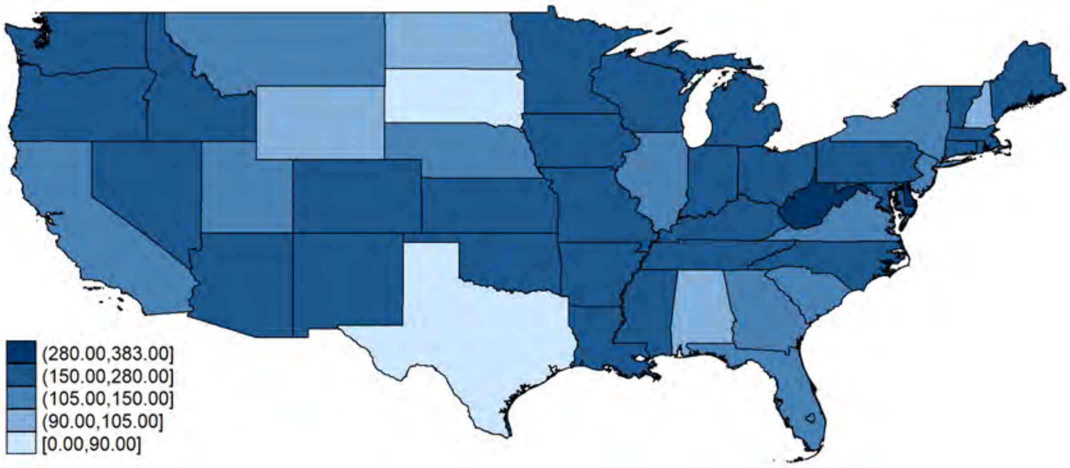
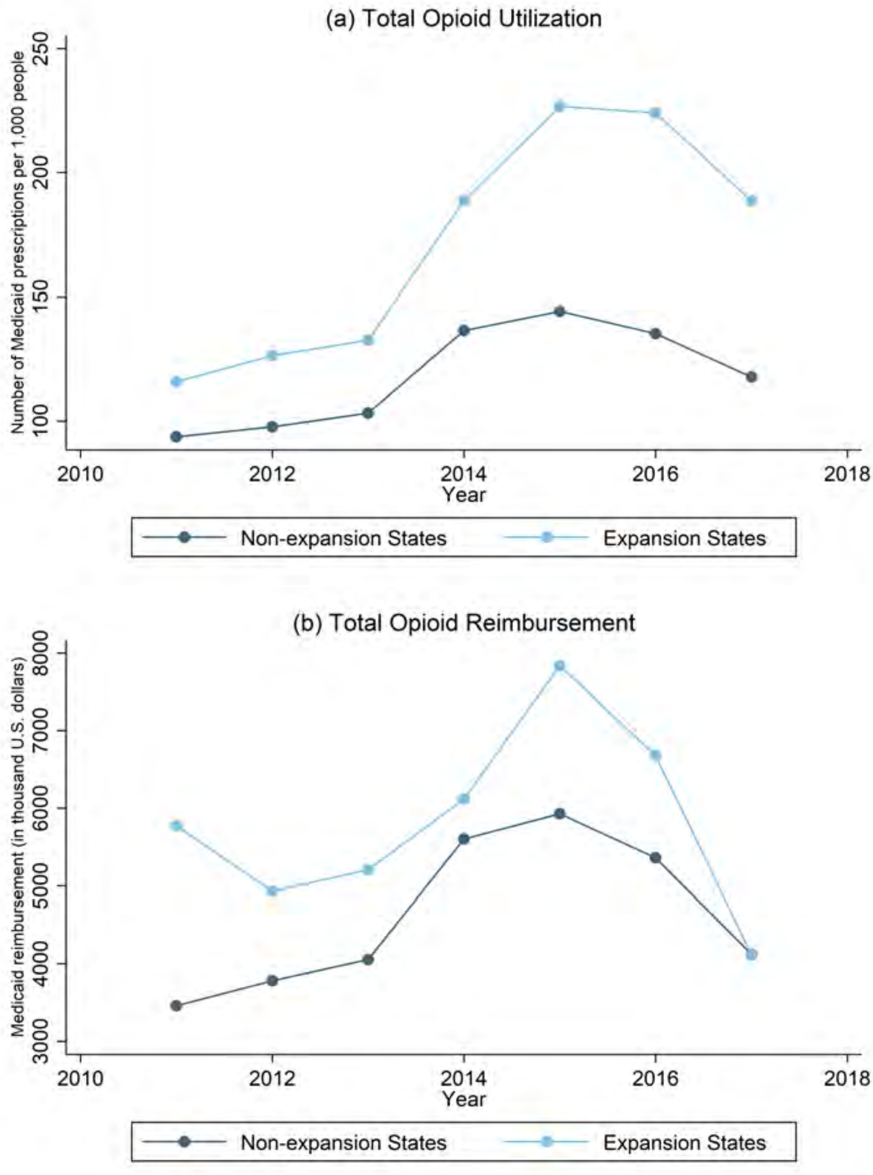
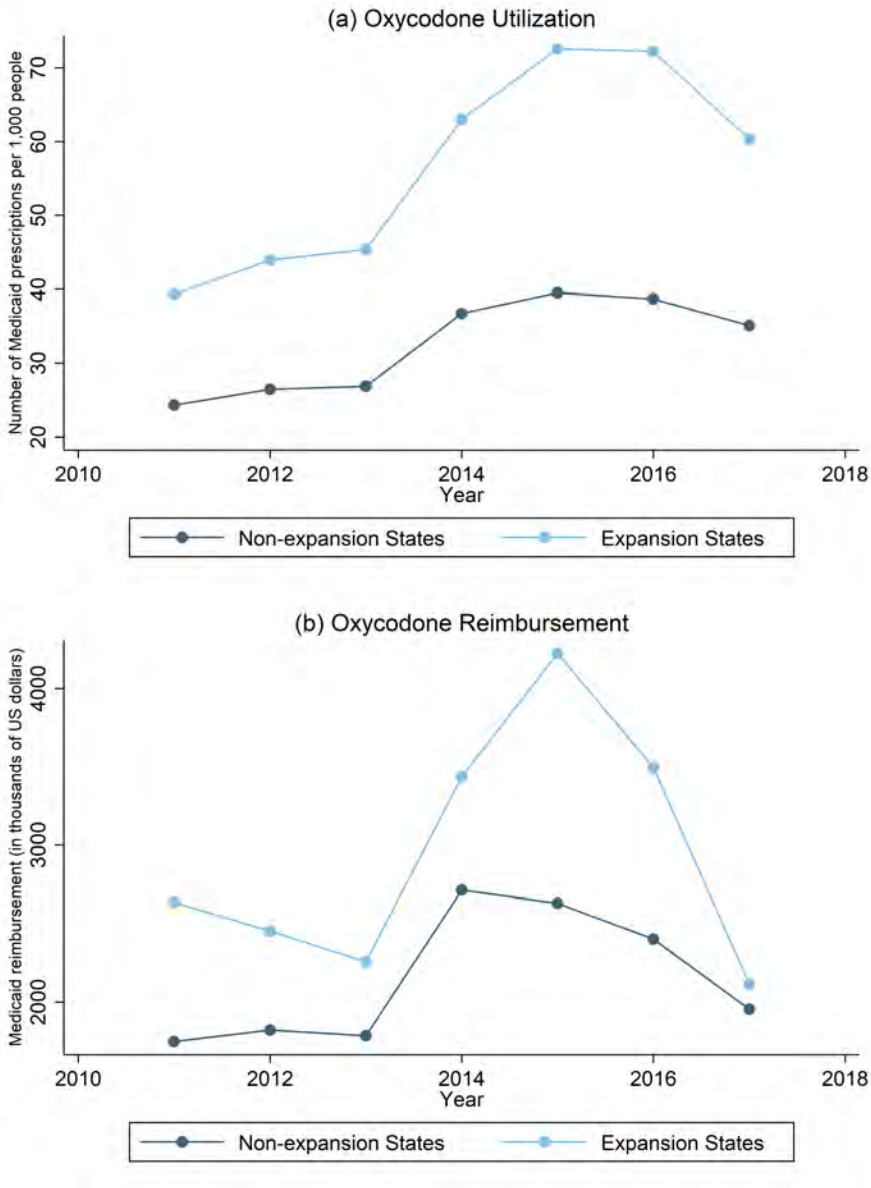


Figure 3: Medicaid utilization and reimbursement of opioids among treatment and control states, 2011–2017: Total



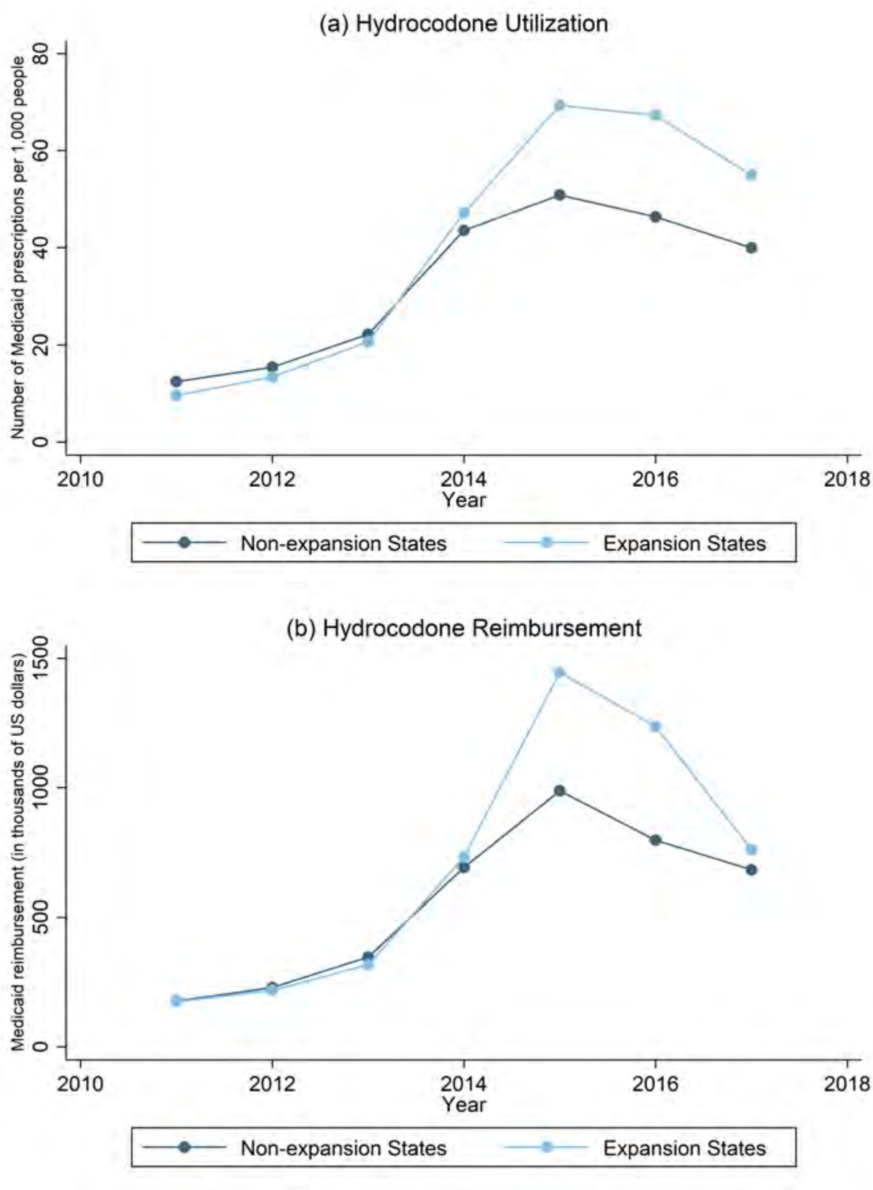
Notes: Medicaid expansion status follows Henry Kaiser Family Foundation (2019). Utilization measures are weighted by state population ages 19–64.

Figure 4: Medicaid utilization and reimbursement of opioids among treatment and control states, 2011–2017, by drug: Oxycodone



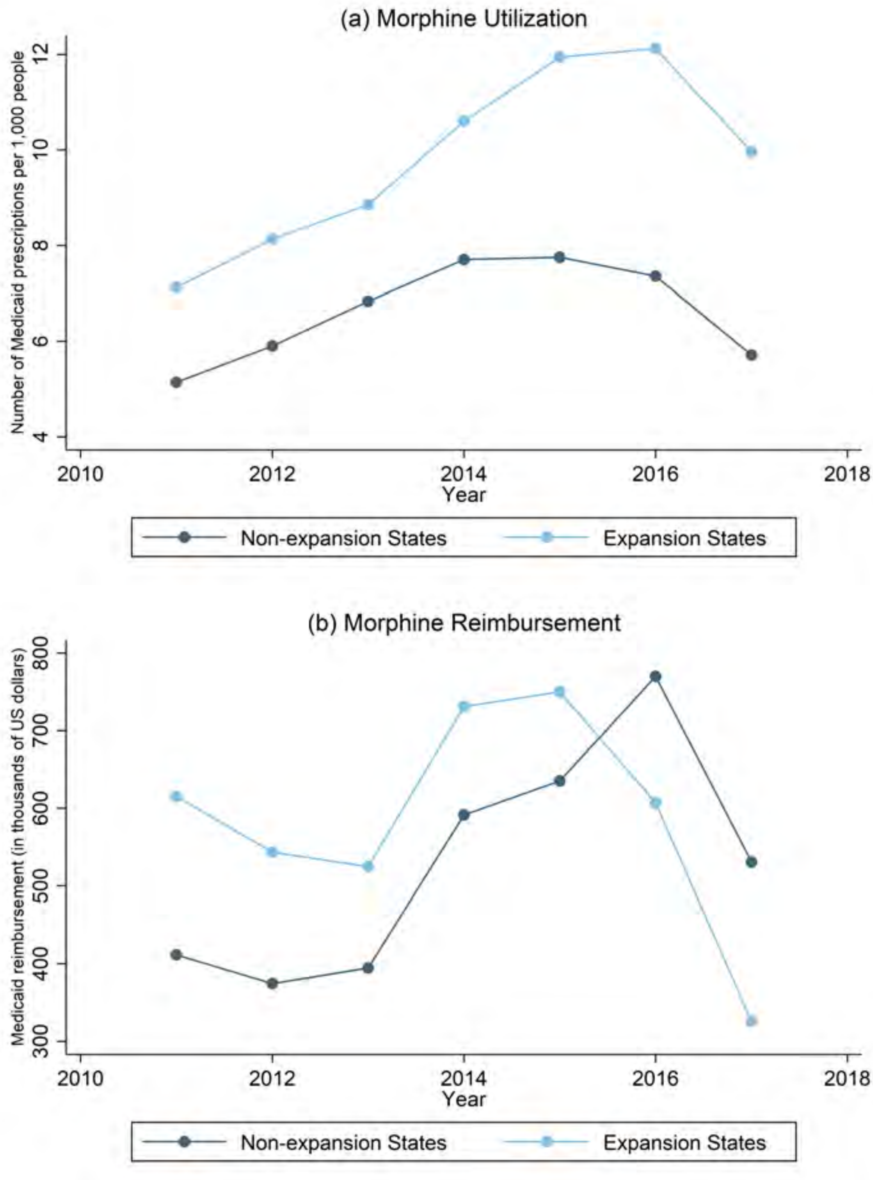
*N*otes: Medicaid expansion status follows Henry Kaiser Family Foundation (2019). Utilization measures are weighted by state population ages 19 - 64.

Figure 5: Medicaid utilization and reimbursement of opioids among treatment and control states, 2011–2017, by drug: Hydrocodone



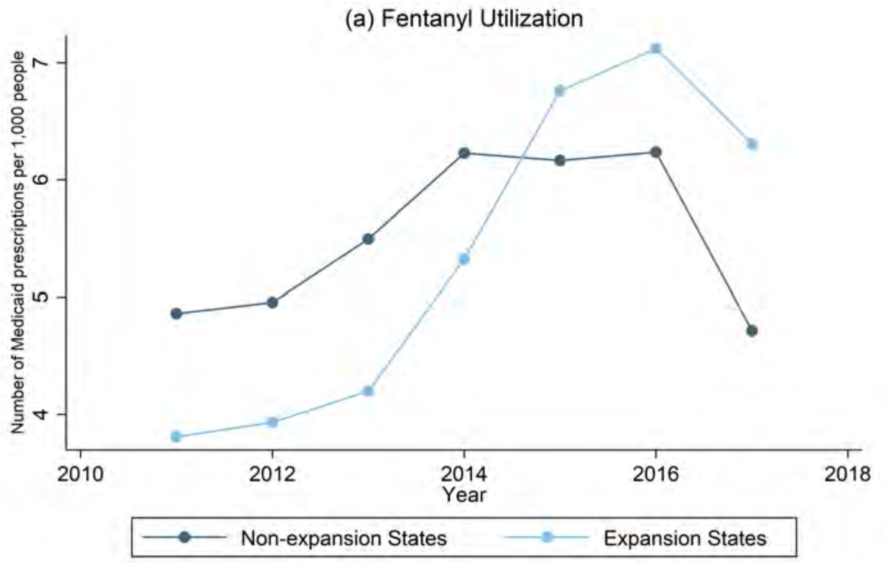
*N*otes: Medicaid expansion status follows Henry Kaiser Family Foundation (2019). Utilization measures are weighted by state population ages 19 - 64.

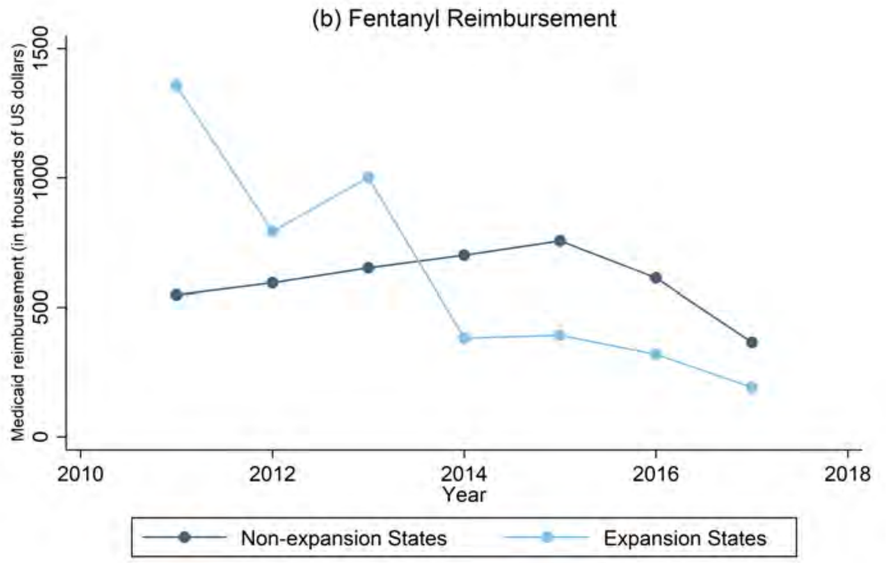
Figure 6: Medicaid utilization and reimbursement of opioids among treatment and control states, 2011–2017, by drug: Morphine



*N*otes: Medicaid expansion status follows Henry Kaiser Family Foundation (2019).
Utilization measures are weighted by state population ages 19–64.

Figure 7: Medicaid utilization and reimbursement of opioids among treatment and control states, 2011–2017, by drug: Fentanyl





*N*otes: Medicaid expansion status follows Henry Kaiser Family Foundation (2019). Utilization measures are weighted by state population ages 19–64.

Table 1: State Medicaid expansion years

State	Year	State	Year	State	Year	State	Year
Alabama	N/A	Illinois	2014	Montana	2016	Rhode Island	2014
Alaska	2015	Indiana	2015	Nebraska	N/A	South Carolina	N/A
Arizona	2014	Iowa	2014	Nevada	2014	South Dakota	N/A
Arkansas	2014	Kansas	N/A	New Hampshire	2014	Tennessee	N/A
California	2011	Kentucky	2014	New Jersey	2011	Texas	N/A
Colorado	2014	Louisiana	2016	New Mexico	2014	Utah	N/A
Connecticut	2010	Maine	N/A	New York	1997	Vermont	2006
Delaware	1996	Maryland	2014	North Carolina	N/A	Virginia	N/A
D.C.	2010	Massachusetts	2006	North Dakota	2014	Washington	2011
Florida	N/A	Michigan	2014	Ohio	2014	West Virginia	2014
Georgia	N/A	Minnesota	2011	Oklahoma	N/A	Wisconsin	N/A
Hawaii	2014	Mississippi	N/A	Oregon	2014	Wyoming	N/A
Idaho	N/A	Missouri	N/A	Pennsylvania	2015		

Notes: (1) The ACA Medicaid and state own expansion years obtained from The Henry and Kaiser Family Foundation and state Medicaid websites, respectively.
(2) CA, CT, D.C., MN, NJ, and WA are the early opt-in states via a Section 1115 Waiver.
(3) D.C., DE, MA, NY, and VT have their own expansion prior to the ACA and also expand Medicaid in 2014.

Table 2: Descriptive statistics (2013) - by Medicaid expansion status

	(1) Full sample		(2) Expansion		(3) Non-expansion	
	mean	sd	mean	sd	mean	sd
Opioid utilization						
Per 1,000 people ages 19–64						
Total prescriptions	121.71	48.37	134.69	52.96	107.12	38.68
Morphine prescriptions	8.01	4.92	8.55	5.34	6.96	3.79
Hydrocodone prescriptions	21.85	12.32	22.26	12.60	21.17	11.83
Oxycodone prescriptions	40.44	23.76	46.98	24.77	27.79	15.09
Fentanyl prescriptions	4.51	3.39	4.05	2.94	5.27	3.91
Total Reimbursements	4,780	5,178	4,256	2,649	5,369	7,047
Total MMEs	111,057	59,356	124,295	62,836	88,760	46,369
Per 1,000 enrollees						
Total prescriptions	453.68	148.20	471.73	145.39	433.37	151.78
Total Reimbursements	18,616	22,422	14,878	7,760	22,823	31,463
Total MMEs	412,241	189,761	444,270	196,677	358,298	168,853
State characteristics						
Unemployment rate	6.79	1.75	7.23	1.87	6.36	1.54
Poverty rate	0.12	0.03	0.12	0.03	0.13	0.04
Percent female	0.51	0.01	0.51	0.01	0.51	0.01
Percent white	0.77	0.14	0.75	0.16	0.79	0.11
Percent uninsured	18.71	5.49	16.89	5.84	20.46	4.60
State minimum wage	7.42	0.71	7.68	0.72	7.17	0.62
Fr. of state house that is Democratic	0.47	0.18	0.60	0.15	0.34	0.10
Fr. of state senate that is Democratic	0.46	0.20	0.60	0.17	0.33	0.11
Share MCO	0.38	0.37	0.48	0.38	0.28	0.34
Opioid-related policies						
PDMP-mandate	0.16	0.37	0.24	0.44	0.08	0.27
Pain clinic laws	0.20	0.40	0.13	0.34	0.32	0.48
Recreational marijuana laws	0.04	0.20	0.06	0.25	0.00	0.00
Observations	51		25		26	

Notes: Expansion status is based on whether the state's Medicaid is expanded in January 2014. Medicaid reimbursements are measured in 2011 dollars. Table excludes prescription drug time and dosage limit laws because states did not start to adopt these laws until 2016.

Table 3: The effect of the Medicaid expansion on opioid utilization

	(1)	(2)	(3)
Panel A			
Prescriptions per 1,000 people	55.558***	59.447***	60.280***
	(14.385)	(11.943)	(11.821)
Prescriptions per 1,000 enrollees	71.113**	74.595**	77.446**
	(28.124)	(29.122)	(28.960)
Panel B			
Reimbursement per 1,000 people	957.936**	928.554*	973.535**
	(451.335)	(492.101)	(468.063)
Reimbursement per 1,000 enrollees	249.060	8.801	196.205
	(1570.249)	(1663.017)	(1545.167)
Panel C			
MMEs per 1,000 people	25010.772***	25387.152***	26069.943***
	(7960.779)	(8543.923)	(8456.112)
MMEs per 1,000 enrollees	2262.045	-247.108	2282.239
	(27300.804)	(29931.711)	(29256.652)
State & year FEs	Y	Y	Y
State characteristics	N	Y	Y
Opioid-related policies	N	N	Y
Observations	357	357	357

Notes: All specifications are weighted by state population ages 19–40. Standard errors in parentheses are adjusted for heteroskedasticity and are clustered by state. Reimbursement is measured in 2011 dollars. MMEs are calculated as: *drug strength*$\times$*morphine equivalent factors*$\times$*total units.*

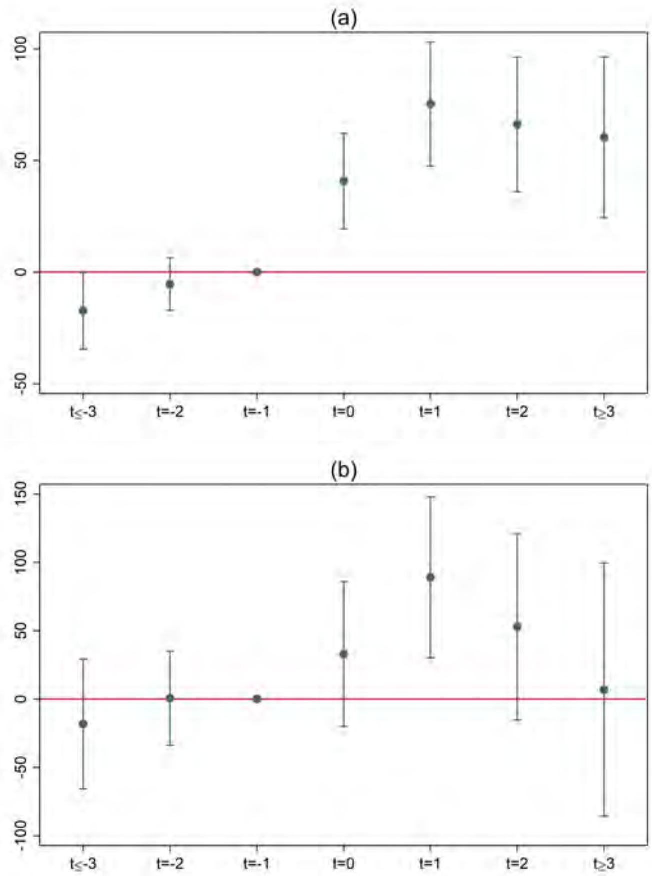
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Table 4: The effect of the Medicaid expansion on opioid utilization by commonly prescribed drugs

	(1) Morphine	(2) Hydrocodone	(3) Oxycodone	(4) Fentanyl	(5) Other
Panel A - Per-population measures					
Prescriptions	1.194	31.992***	14.576***	1.652**	10.866**
	(0.775)	(8.546)	(5.363)	(0.708)	(4.519)
Mean 2013	8.01	21.85	40.44	4.51	
	(4.92)	(12.32)	(23.76)	(3.39)	
Reimbursement	-56.258	468.515***	515.767*	-80.046	125.074
	(122.681)	(152.961)	(261.047)	(146.439)	(101.250)
Mean 2013	465.82	336.59	2057.67	697.78	
	(522.41)	(186.93)	(1,182.66)	(1,859.14)	
MMEs	-716.384	11729.308**	12239.714**	-102.986	2909.256*
	(2115.452)	(4809.603)	(4766.882)	(831.421)	(1653.828)
Mean 2013	18679.82	10531.76	59057.28	9092.48	
	(13,854.02)	(6,423.58)	(35,317.54)	(6,122.14)	
Panel B - Per-enrollee measures					
Prescriptions	-2.405	61.224***	9.913	2.765	5.947
	(2.174)	(21.859)	(9.405)	(1.716)	(12.426)
Mean 2013	29.81	80.81	151.52	18.08	
	(16.72)	(45.25)	(83.23)	(15.57)	
Reimbursement	-540.852	872.068**	410.287	-587.337	37.694
	(416.208)	(394.444)	(663.851)	(670.510)	(292.163)
Mean 2013	1693.68	1248.91	7876.98	2913.59	
	(1591.50)	(745.82)	(4603.81)	(8298.91)	
MMEs	-13378.789*	20826.326	-1775.921	-4055.733	594.021
	(7366.175)	(12619.923)	(11479.611)	(3064.666)	(4802.230)
Mean 2013	67629.77	38787.02	221823.46	33146.31	
	43489.96	23521.02	124039.20	18443.07	
Observations	357	357	357	357	357

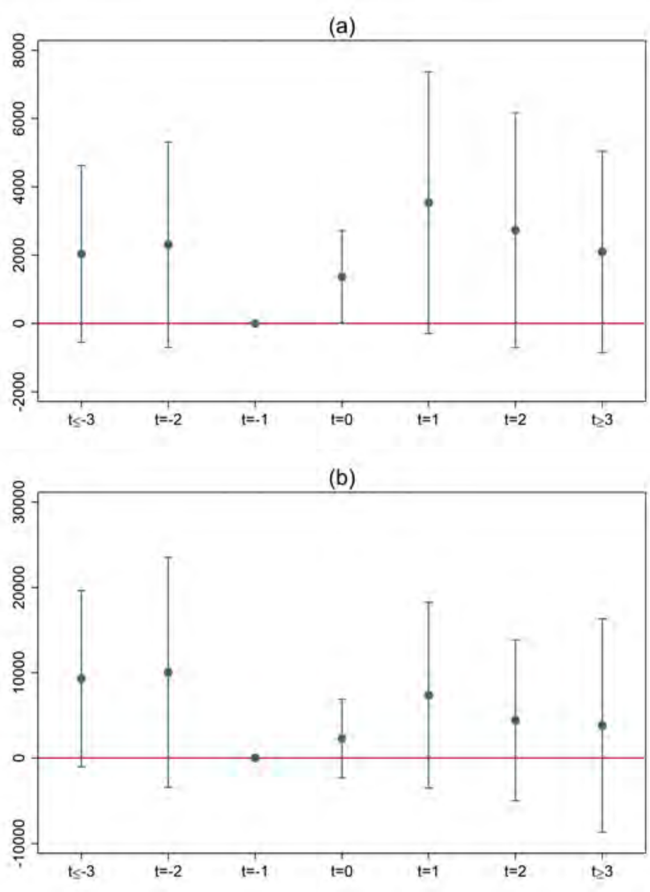
Notes: All specifications are weighted by state population ages 19–40. Standard errors in parentheses are adjusted for heteroskedasticity and are clustered by state. MMEs are calculated as: *drug strength*$\times$*morphine equivalent factors*$\times$*total units.* Full-sample 2013 means and standard deviations are reported for reference.
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Figure 8: Event-study results: Effects of the Medicaid expansions on opioid prescriptions.



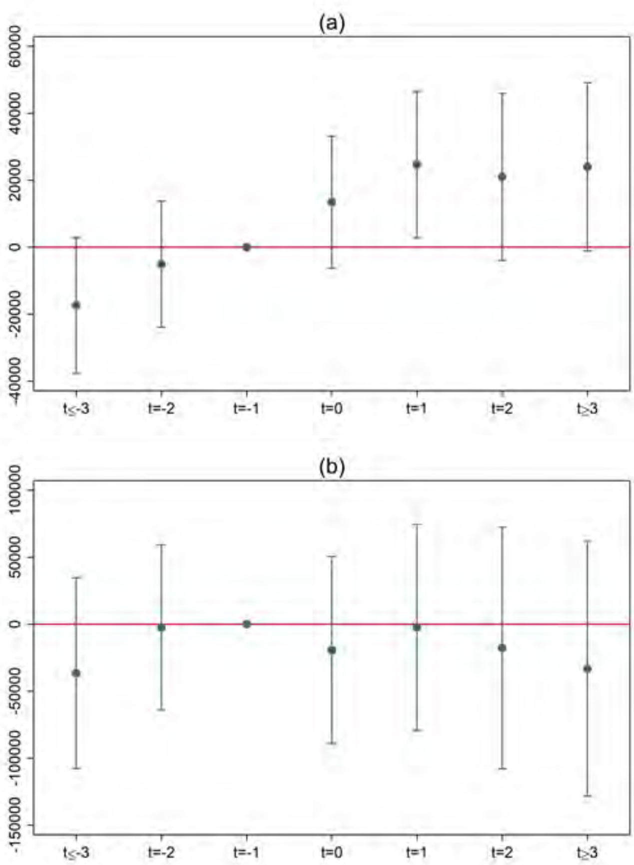
Notes: Estimates and 95% confidence intervals are results from estimating equation (2). *t=0* is the year of expansion, *t=-1* is the reference year. Dependent variables are state-year counts of prescriptions and are *(a) divided by state population ages 19–64 (1,000s), (b) and divided by the number of enrollees (1,000s).*

Figure 9: Event-study results: Effects of the Medicaid expansions on opioid reimbursement.



Notes: Estimates and 95% confidence intervals are results from estimating equation (2). Reimbursement is measured in 2011 dollars. *t=0* is the year of expansion, and *t=-1* is the reference year. Dependent variables are state-year aggregate Medicaid reimbursement and *(a) divided by state population ages 19–64 (1,000s), (b) and divided by the number of enrollees (1,000s).*

Figure 10: Event-study results: effects of the Medicaid expansions on opioid use, in MMEs.



Notes: Estimates and 95% confidence intervals are results from estimating equation (2). MMEs are calculated as: *drug strength*$\times$*morphine equivalent factors*$\times$*total units*. *t=0* is the year of expansion, and *t=-1* is the reference year. Dependent variables are sum of state-year opioid use measured in morphine milligram equivalents (MMEs) and are *(a) divided by state population ages 19–64 (1,000s), (b) and divided by the number of enrollees (1,000s).*

Table 5: Robustness checks for potential confounding factors

	Share MCO	Political controls	Share of enrollees ages 26–54
Panel A - Per-population measures			
Prescriptions	58.6***	59.7***	59.6***
	(12.1)	(11.4)	(11.5)
Reimbursements	1,024.6*	930.1*	917.6*
	(565.5)	(468.3)	(458.4)
MMEs	26,304***	25,829***	25,241***
	(8,185)	(8,007)	(8,077)
Panel B - Per-enrollee measures			
Prescriptions	74.6**	76.7**	76.1***
	(31.4)	(29.0)	(27.4)
Reimbursements	97.8	15.4	42.5
	(1,897)	(1,618)	(1,513)
MMEs	1,735	1,662	-45
	(29,371)	(29,711)	(27,828)
Observations	357	343	357

Notes: All specifications control for state opioid-related policies and include state and year fixed effects. Regressions are weighted by state population ages 19–40. Standard errors in parentheses are adjusted for heteroskedasticity and are clustered by state.
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Table 6: Specification sensitivity checks

	Excluded early expansion states	Census Div. & year interactions	Unweighted	Control for pre-trends
Panel A - Per-population measures				
Prescriptions	56.9***	49.3***	66.6***	56.0***
	(11.6)	(11.0)	(13.1)	(11.9)
Reimbursements	872.2*	866.6	1145.1	1018.3**
	(478.5)	(633.3)	(1071.5)	(390.5)
MMEs	24,841***	21,175***	28,172***	23,513**
	(8,829)	(7,207)	(8,470)	(10,977)
Panel B - Per enrollee measures				
Prescriptions	70.7**	28.6	68.7**	76.3**
	(28.6)	(22.7)	(27.4)	(29.3)
Reimbursements	89.8	-904.6	-1,441.2	721.0
	(1,539.9)	(1,826.0)	(3,336.0)	(1,260.6)
MMEs	-475	-24,229	-15,258	5,456
	(29,832)	(22,574)	(24,135)	(23,645)
Observations	322	357	357	357

Notes: All specifications control for state opioid-related policies and include state and year fixed effects. Regressions are weighted by state population ages 19–40. Standard errors in parentheses are adjusted for heteroskedasticity and are clustered by state.
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Table 7: State opioid-related polices

State	Prescription drug time and dosage limit laws			Must-access PDMP	Pain clinic Regulation	Recreational marijuana law
	Year	Day limit	Amount limit			
Alabama					2013	
Alaska	2017	7		2017		2014
Arizona						
Arkansas				2017		
California						2016
Colorado						2012
Connecticut	2016	7		2015		
Delaware	2017	7		2012		
District of Columbia						2014
Florida					2010	
Georgia				2014	2013	
Hawaii	2016	30				
Idaho						
Illinois	2012	30		2018		
Indiana	2017	7		2014		
Iowa						
Kansas						
Kentucky	2017	3		2012	2012	
Louisiana	2017	7		2008	2006	
Maine	2017	7	100 MME/day			2016
Maryland	2017	None	Lowest effective dose	2018		
Massachusetts	2016	7		2014		2016
Michigan						2018
Minnesota	2017	4		2017		
Mississippi					2011	
Missouri	1988	30				
Montana						
Nebraska						
Nevada	2017	14	90 MME/day	2017		2016
New Hampshire	2017	7	Lowest effective dose	2016		
New Jersey	2017	5	Lowest effective dose	2015		
New Mexico				2015		
New York	2016	7				
North Carolina	2018	5				
North Dakota						
Ohio	2017	7	30 MME/day	2015		
Oklahoma				2015		
Oregon						2014
Pennsylvania	2017	7		2017		
Rhode Island	2017	20 doses	30 MME/day	2016		
South Carolina	2007	31		2017		
South Dakota						
Tennessee	2013	30		2013	2011	
Texas	2013	30		2019	2009	
Utah	2017	7		2017		
Vermont	2017	Varies	Varies	2015		2018
Virginia	2017	7		2015		
Washington						2012
West Virginia					2012	
Wisconsin						
Wyoming					2016	

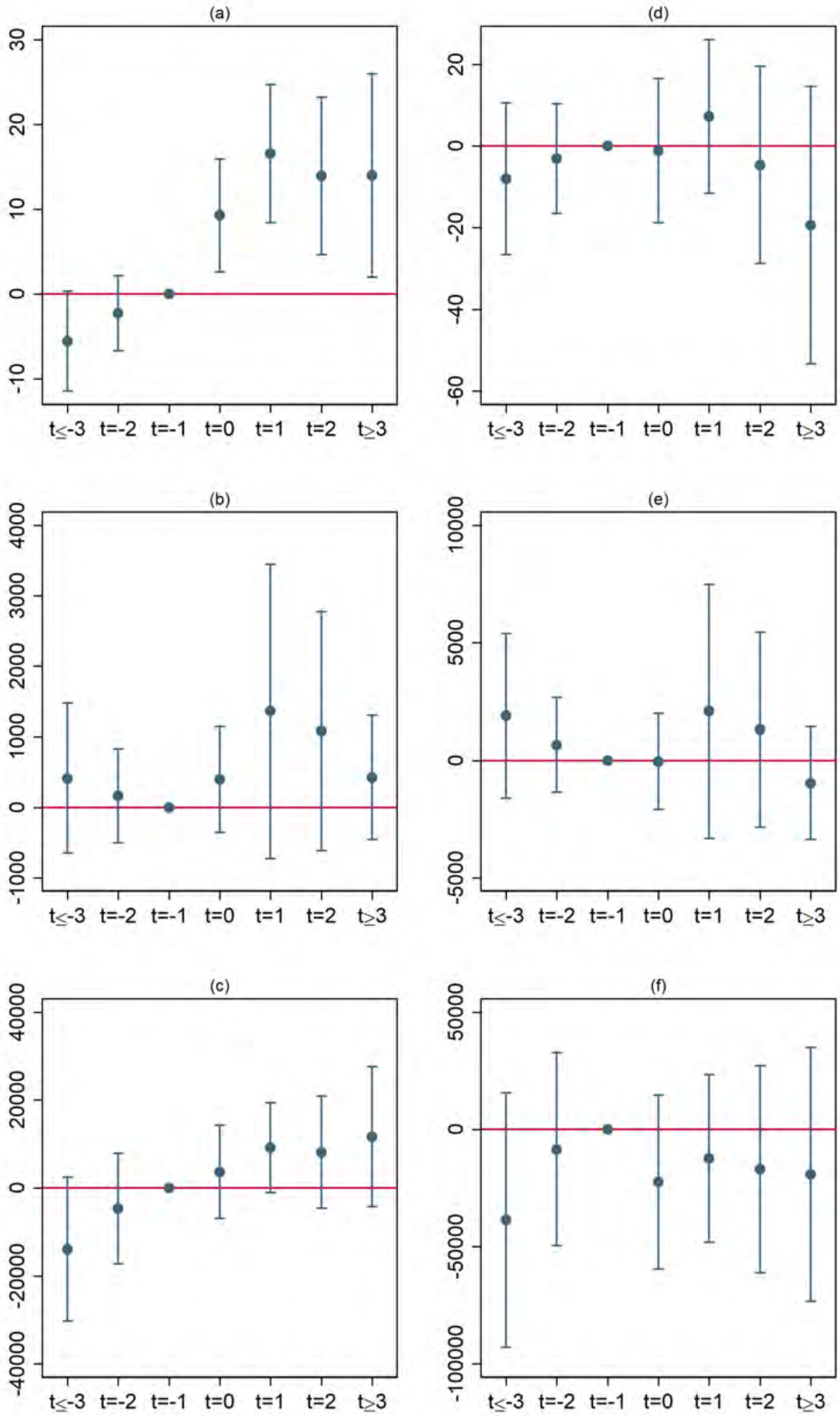
Notes: Table reports the effective years of states' opioid-related regulations. Prescription drug time and dosage limit laws limit the number of days and/or amount of opioids prescribed to first-time patients.

Table 8: Common prescription opioids

Generic	Brand name
buprenorphine	Belbuca
	Butrans
butorphanol	
codeine	
fentanyl	Actiq
	Duragesic
	Fentora
	Subsys
hydrocodone	Lortab
	Norco
	Vicodin
	Reprexain
hydrocodone bitartrate	Hysingla
	Zohydro
hydromorphone	Dilaudid
	Exalgo
meperidine	Demerol
methadone	Dolophine
morphine sulfate	Duramorph
	Infumorph
	MorphaBond
	Embeda
	MS Contin
nalbuphine	
oxycodone	Oxycontin
	Xartemis
	Percocet
	Xtampza
	Roxicodone
oxymorphone	Opana
tapentadol	Nucynta
tramadol	Ultram

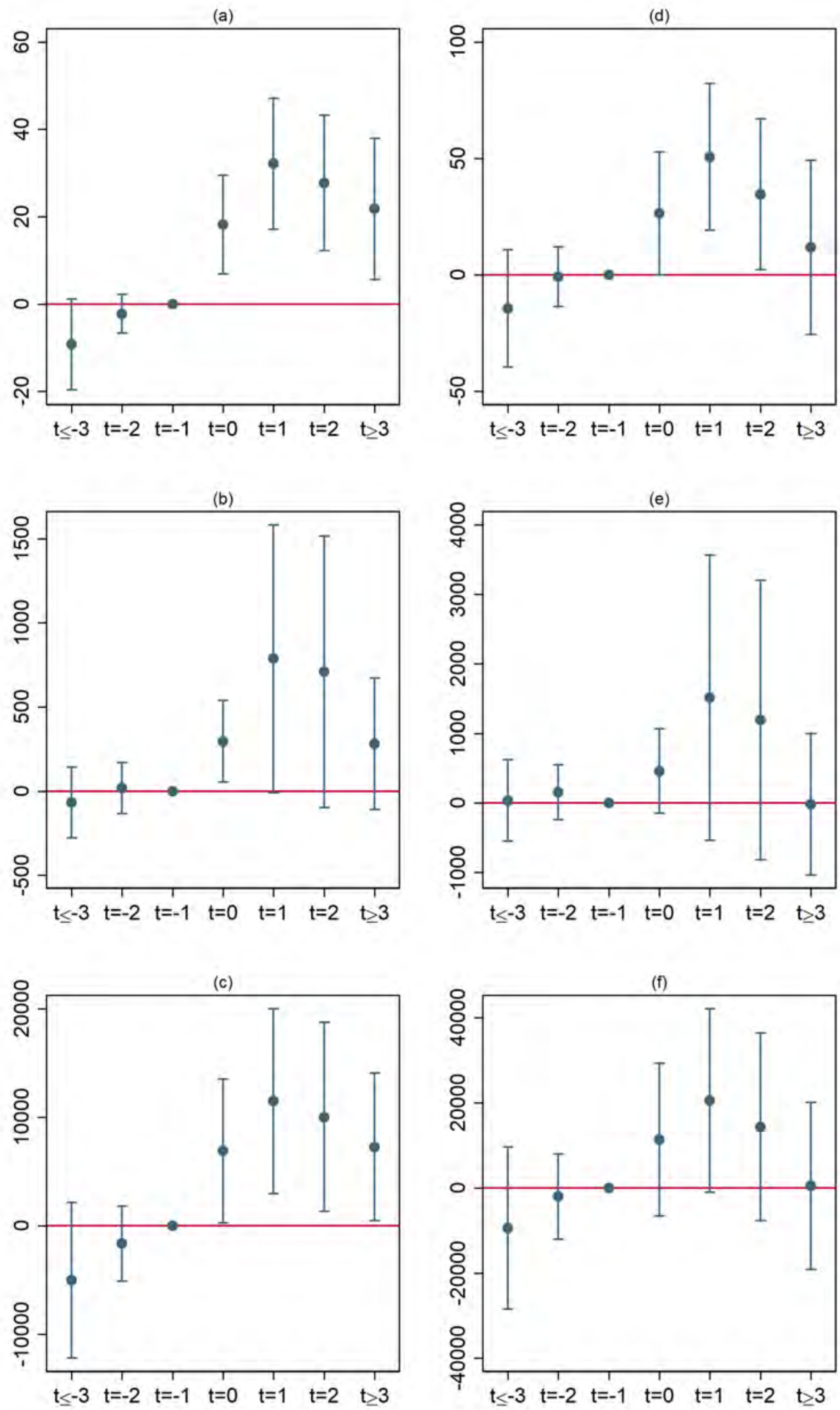
Notes: This list contains common opioid drug names with non-zero utilization. Substance names are obtained from Medicaid Opioid Drug Lists and the Monthly Prescribing Reference. For a full list of prescription opioids used in this paper, visit *www.cms.gov*.

Figure 11: Event-study results: Effects of the Medicaid expansions on Oxycodone use



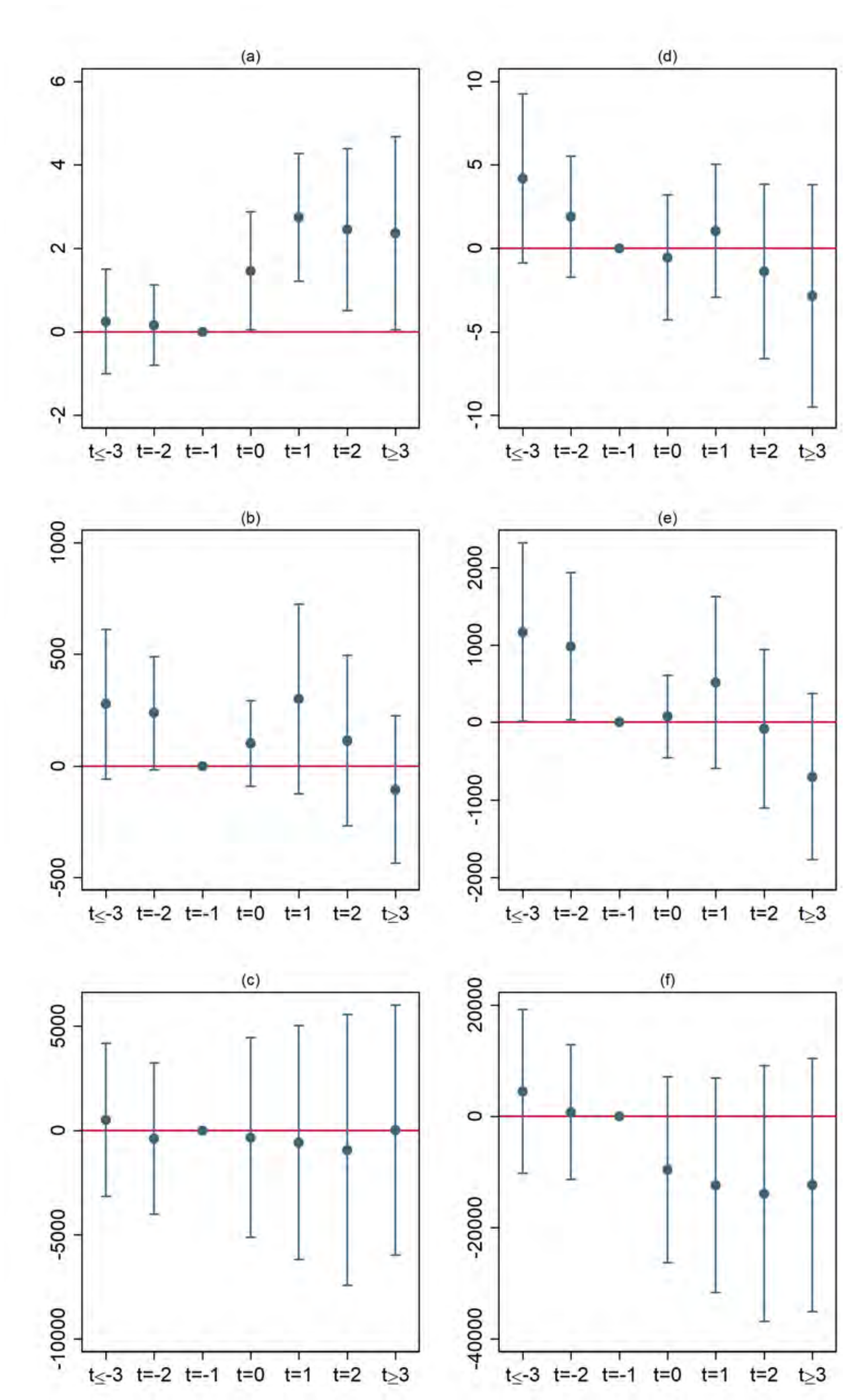
Notes: Estimates and 95% confidence intervals are results from estimating equation (2). *t=0* is the year of expansion, and *t=-1* is the reference year. Dependent variables: per population (1,000 people ages 19–64) (a) number of prescriptions, (b) reimbursements, (c) MMEs, and per enrollee (in 1,000s) (d) number of prescriptions, (e) reimbursements, (f) MMEs. Reimbursement is measured in 2011 dollars.

Figure 12: Event-study results: Effects of the Medicaid expansions on hydrocodone use



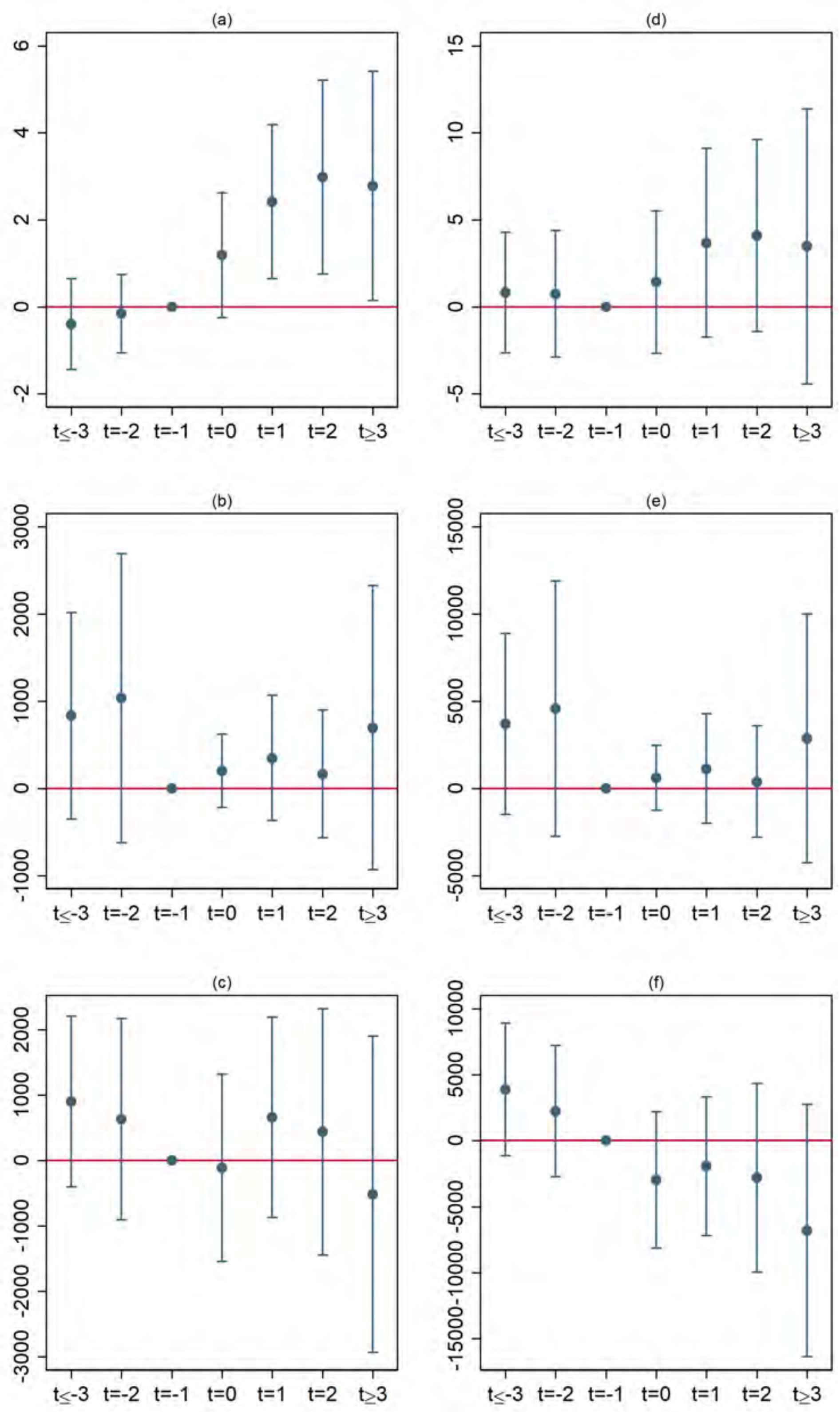
Notes: Estimates and 95% confidence intervals are results from estimating equation (2). *t=0* is the year of expansion, and *t=-1* is the reference year. Dependent variables: per population (1,000 people ages 19–64) (a) number of prescriptions, (b) reimbursements, (c) MMEs, and per enrollee (in 1,000s) (d) number of prescriptions, (e) reimbursements, (f) MMEs. Reimbursement is measured in 2011 dollars.

Figure 13: Event-study results: effects of the Medicaid expansions on morphine use



Notes: Estimates and 95% confidence intervals are results from estimating equation (2). *t=0* is the year of expansion, and *t=-1* is the reference year. Dependent variables: per population (1,000 people ages 19–64) (a) number of prescriptions, (b) reimbursements, (c) MMEs, and per enrollee (in 1,000s) (d) number of prescriptions, (e) reimbursements, (f) MMEs. Reimbursement is measured in 2011 dollars.

Figure 14: Event-study results: effects of the Medicaid expansions on fentanyl use



Notes: Estimates and 95% confidence intervals are results from estimating equation (2). *t=0* is the year of expansion, and *t=-1* is the reference year. Dependent variables: per population (1,000 people ages 19–64) (a) number of prescriptions, (b) reimbursements, (c) MMEs, and per enrollee (in 1,000s) (d) number of prescriptions, (e) reimbursements, (f) MMEs. Reimbursement is measured in 2011 dollars.