The Relationship between Increased Stability and Coverage from Public Health Insurance and Opioid Miuse among Parenting Women: Study from The Affordable Care Act

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Abstract

In this paper, I examine the impact that increased public insurance continuation for new mothers may have on use among parenting women expecting extended coverage. This study compares the changes in opioid and substance misuse between income groups with and without Medicaid expansions under the Affordable Care Act. I identify women most likely to benefit from this policy by using survey information on socioeconomic status and age. Using data from the National Survey of Drug Use and Health and the Current Population Survey cross-sectional data, I find that before 2014, misuse trends among identified income groups did not differ significantly, but after 2014 there is a significant yet small decrease among lower income mothers who experience higher growth in Medicaid coverage after 2014. Parenting women with income below-64% FPL experience a 2.9-percentage-point decrease and those with income 64–138% FPL experience a 2-percentage-point decrease in opioid misuse rate.

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1 Introduction

An effective analgesic, opioids are some is one of the most pervasive prescribed medications in the United States. However, misuse and overdose have reached an alarming stage in the United States, with mortality from ovedose counts quadrupling since 2006 (Schiff et al., 2018), surpassing that from motor vehicle crashes (Hadland et al., 2017). In 2016, prescription opioid overdose deaths comprised approximately 70% of fatal prescription drug overdoses (Florence et al., 2016). The diagnosis rate of opioid use disorder (OUD) increased nearly 6–fold from 2001 to 2014 (from 0.26 per 100,000 person-years to 1.51 per 100,000 person-years), with screening results concentrated among eighteen-and-above young adults, though rises occurred concurrently in all age groups (Hadland et al., 2017). After their prescriptions, those suffering from OUD may see increased tolerance (reduced analgesia) and hyperalgesia (increased sensitivity to pain) (Klaman et al., 2017).

Although white non Hispanic, middle age (45–54) males with high school diploma or lower (Case and Deaton, 2017) have been highlighted as the demographic with the highest misuse and mortality rate, other vulnerable groups face demographic-unique hardships that could subject them to opioid misuse. Particularly, exposure among pregnant women and new mothers has also grown substantially throughout the course of the epidemic. Since 2002, prescription opioid use and misuse have significantly increased among men and women (pregnant and nonpregnant). In 2011–2012, the number of reports from women aged 15 to 44 past-month nonmedical use of psychotherapeutics, OxyContin (oxycodone) type increased to 98,000, or 5.4% (Klaman et al., 2017). Opioid use among pregnant women more than doubled from 8.6% in 1995 to 20.1% in 2009 (CDC, 2018; Yazdy et al., 2013). Furthermore, opioid use and OUD are heterogeneous across women's pregnancy and postpartum cycles. While prenatal opioid and opioid agonist prescriptions require careful deliberation to ensure safety for both mothers and infants, postpartum mothers in particular receive less attention and care, while also facing higher risk of discontinuation in employment and health insurance statuses. The surgical procedures in delivery such as c-section may also involve analgesic use, adding another channel of exposure for new mothers (Bateman et al., 2017; Osmundson et al., 2017). Some studies have confirmed that women prescribed opioid after c-section without counselling on proper use are more prone to OUD (Bateman et al., 2016), with others highlighting that most women undergoing c-section receive opiate prescriptions in excess of the needed amountBateman et al. (2017); Osmundson et al. (2017).

The economic and societal burdens of the epidemic include healthcare costs, productivity loss, of OUD and overdose mortality can amount to total $78.5 billion, a third of which goes to healthcare and treatment costs (Florence et al., 2016). Furthermore, substance exposure and overdose among mothers can result in complications to birth, postpartum depression, and long-term developmental patterns among children. Particularly, overdose has accounted for approximately 11–20% of pregnancy mortality (Schiff et al., 2018).

Thus, understanding and solving the crisis requires targeted policies that not only regulate the supply and use of analgesics but also provide improvements in overall living conditions so that long-term behavioral patterns can be altered. Public programs such as the Affordable Care Act (ACA) and especially Medicaid serve among such gallant efforts. Simultaneously, despite its purpose to erase categorical eligibility (Meinhofer et al., 2021; MACPAC, 2018; KFF, 2021), Medicaid expansion under the ACA may still affect different demographic groups differently. Particularly, pre-ACA Medicaid already covered 40% of all deliveries in the US (MACPAC, 2018; Clark, 2020) but did not cover mothers beyond 60 days post-delivery. Therefore, ACA expansion may prolong and stabilize insurance status for a portion of women eligible for coverage during pregnancy. In contrast, one of the most significant impacts that Medicaid expansion under ACA terms have been the improvement in insurance stability for postpartum women and parents in general. Before the wave of ACA adoption between 2014–2017, approximately 55% of pregnant women previously covered by Medicaid experience a change in insurance status (undergoing either Medicaid-uninsured or Medicaid-privately insured transition) in the postpartum period (Daw et al., 2019). Under the ACA terms, states may choose to expand Medicaid to cover individuals with household income up to 138% of the Federal Poverty Line and to offer treatment for substance use disorders (SUDs), which include OUD. Yet, the impact of Medicaid generosity on the epidemic remains ambiguous, due to the coexistence of multitude risk factors that the program may influence, including rate of prescription, medical use, non-medical use, and illicit substance purchase.

To my knowledge, the literature on substance use disorder among women, particularly pregnant women and new mothers, remains thin, with research seldom examining issues women face postpartum. And while there have been well-established studies on prenatal and postpartum risky health behaviors as well as mortality and morbidity, few directly examine the interaction between Medicaid and analgesic use and misuse. Because a wider time horizon requires controlling for changes in socioeconomic conditions, policies, and interactions among policies, most studies have also focused on the short-term effect of Medicaid expansion. Meinhofer and Witman (2018) provides the most comprehensive study to date for the impact of Medicaid under ACA on the epidemic, but the outcomes only revolve around treatment availability and utilization and do not mention misuse behaviors. Therefore, interpretation of their findings should be conducted with care.

This paper proceeds as follows: Section 2 reviews the backgrounds and relationship between the opioid epidemic and the Affordable Care Act, focusing on the literature regarding the impacts that prenatal and postpartum women experience; section 3 presents data used in analysis; section 4 discusses empirical strategies; section 5 reports on the results; section 6 discusses further robustness checks; and section 7 concludes.

2 Background

2.1 Opioid crisis

2.1.1 Current situation

The first wave of the opioid crisis in the United States emerged with the rise of opioids prescription in the 1990s, with overdose deaths involving prescription opioids (including both natural and semi-synthetic opioids and methadone) increasing since at least 1993. The second wave began in 2010, with rapid increases in overdose deaths involving heroin. The third wave began in 2013, with significant increases in overdose deaths involving synthetic opioids, particularly those involving illicitly manufactured fentanyl. The market for illicitly manufactured fentanyl continues to change, and it can be found in combination with heroin, counterfeit pills, and cocaine (Dasgupta et al., 2018).

Given their specific needs for pregnancy-induced and chronic pain suppression, women in prenatal and postpartum stages may exhibit different patterns in opioid use and misuse incidents. Analyzing the Pregnancy Risk Assessment Monitoring System (PRAMS), CDC (2020) records that 7% of all pregnant women in the US reported using prescription opioids during pregnancy, of which 32% report not receiving counseling from a healthcare provider about the potential effects of prescription opioid use on a baby, 20% report opioids misuse either from non-health sources or for reasons other than pain relief, and 27% express desires to abstain or limit their uses. The consequences of prenatal opioid exposure and misuse include adverse impacts on mothers and on infants, such as preterm birth, stillbirth, maternal mortality, and neonatal abstinence syndrome (NAS) – a group of withdrawal symptoms most common among newborns exposed to opioid in utero CDC (2020). Newborns with NAS may exhibit an amalgamation of symptoms, ranging from central nervous system irritability (most notably tremors, increased muscle tone, high-pitched crying, and seizures), to gastrointestinal dysfunction (feeding difficulties), and temperature instability (Ko et al., 2016; Patrick et al., 2015).

Using data from the Agency for Healthcare Research and Quality's (AHQR) Healthcare Cost and Utilization Project (HCUP) State Inpatient Databases, Haight et al. (2018) reports that the number of pregnant women with opioid use disorder (OUD) at labor and delivery on average quadruples from 1.5 to 6.5 cases per 1,000 per delivery hospitalizations in all 28 states with at least three years of data available for analysis from 1999 to 2014. Correspondingly, four times as many infants were born with neonatal abstinence syndrome (NAS) in 2012 than in 1999 (Haight et al., 2018; Patrick et al., 2015). However, over the study period, annual increase rates fluctuate substantially across states, where California and Hawaii saw the least rapid rises (growth of less than 0.1 cases per 1,000 each year) while Maine, New Mexico, Vermont, and West Virginia saw the most rapid changes (all with growth of more than 2.5 cases per 1,000 each year). The report also highlights that the reported at-delivery OUD rates also correlate with opioid prescription rates in each state (Haight et al., 2018). This result seems to suggest expansion in treatment postpartum is critical for mothers exposed to opioids during their prenatal periods. Figure 2 shows the trajectory of opioid overdose mortality and death rate among women aged 18–64 and the full population. While death rates among women are lower than the population estimation (and thus lower than that among men), there is still a concerning rise of mortality count and rate over the years.

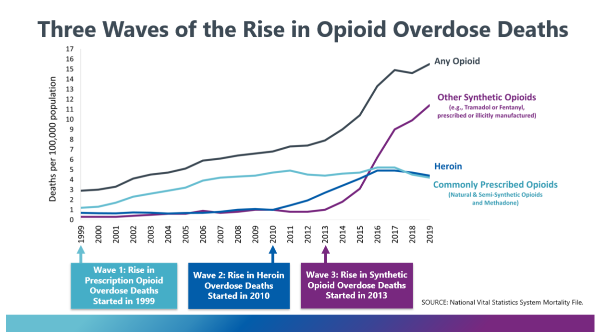
2.1.2 Determinants

From a supply perspective, Alpert et al. (2019) attribute initial cause for the first onset of opioid prescription and overdose crisis in the US to Purdue Pharma's intensive marketing for OxyContin as a safe general (non-cancer) pain-relief use in its attempt to enter the "much larger market for non-cancer pain". Using a difference-in-difference framework with drug prescription triplicate mandates as the instrumental variable for state's varying level of exposure to Purdue Pharma's OxyContin marketing, they estimate that overdose rates in non-triplicate states are 0.25 deaths per 100,000 higher than triplicate states, translating to 2.25 deaths per 100,000 in 2002 and 11.41 per 100,000 in 2017. Furthermore, the authors note that OxyContin market share had a lagged effect on overdose deaths. The effect sizes attained prove to be statistically significant and qualitatively meaningful.

Dasgupta et al. (2018) identify both medical needs and "structural environments" as important determinants for the persistence of the crisis. They highlight patients' increased expectation for fast pain relief, deterioration in musculoskeletal functions among the aging population, obesity, and increase in rate of survivor among cancer patients, and increase in surgery procedure complexity as some of the sources of expansion in demand for prescribed analgesics in the 1990s overdose wave.

Explanations emphasize how limited pain management services from insurers may provide pharmaceutical companies with a market of patients in high demand of affordable and speedy pain relief. On the other hand, lack of access to insurance may disincentivize OUD patients from seeking and maintaining treatment services. Because neither private nor public insurance covered physical pain and psychotherapy before the ACA, pharmaceutical companies found opportunities for proliferation in the chronic pain market (Dasgupta et al., 2018). In the second wave, heroin overdose tripled between 2010 and 2015 to accommodate for expanding demand among individuals who substituted prescribed opioids with heroin due to increased tolerance and dependency (Dasgupta et al., 2018). Particularly, drug firms expanded production in "extended-release formulations, transdermal patches, nasal sprays, and oral dissolving strips, while medical device manufacturers initiated mass production of "novel pain-modulating implants", propelling chronic pain to becoming a thriving market by 2000 (Dasgupta et al., 2018). Finally, the third wave of overdose deaths emerged in 2013 and persists as trafficking allowed for exchange of illicitly produced fentanyl and its analogs – a potent and less bulky product that acted as both a complement and a substitute for "counterfeit pills and heroin" (Dasgupta et al., 2018). Furthermore, the fact that the epidemic has persisted through the interrelation among the waves highlights that prescribed and illicit opioid analgesics act as both complements and substitutes. Figure 1, retrieved from CDC (2021), confirms that starting from 2013, mortality rate of synthetic opioids have increased in proportion to total mortality rate of to opioids, overtaking heroin and prescription opioids to become the leading cause of mortal opioid overdoses per 100,000 persons in 2015.

Figure 1: Three waves of opioid overdose deaths



Source: CDC (2021)

Figure 6, 7, and 8, indicate that there seem to be a reduction or no significant increase in natural opioids such as codeine or morphine and in semy-synthetic opioid misuse for hydrocodone, and oxycodone (OxyContin), while heroin use and hyromorphone misuse rates have risen. On the other hand, figures 9 and 11 indicate that fentanyl misuse, and buprenorphine (in the full sample as well as among those receiving SUD treatments) seem to have risen after 2014. At the same time, rates of methadone misuse and methadone misuse among SUD treatment patients have both decreased after 2014.

From a demand perspective, emerging evidence has pointed to the roles structural environments play in rendering individuals and households more prone to seek opioid analgesics for non-medical purposes. Case and Deaton (2017) have cited structural inequality and economic instability to be catalytic of most non-health demand for analgesics. Particularly, exposure to analgesics via prescription can instigate individuals to misuse and develop opioid use disorder (OUD).

2.1.3 Treatment

Treatment for opioid use disorder (OUD) include detoxification, rehabilitation services, and the use of opioid agonist or antagonist medication-assisted treatment (MAT). Detoxification services deal with the physical and psychological withdrawal symptoms arising from discontinuation in opioid intakes after a long duration of dependence. Rehabilitation services, on the other hand, deliver self-sustained recovery via support services such as behavioral therapy once patients have successfully cut their addiction. In either services, treatment practice can follow the abstinence approach or the maintenance approach. An opioid maintenance approach generally applies to patients unable to completely sever their opioid dependence. As part of the "maintenance approach", both detoxification and rehabilitation may resort to MATs agonists methadone or buprenorphine to attain stabilization and tapering (Meinhofer and Witman, 2018). Therapy may also use opioid antagonist MAT naltrexone as a "abstinence approach".

However, before the ACA, only 1 in 4 individuals with OUD received buprenorphine or naltrexone. Younger individuals, females, and black and Hispanic youth were also less likely to receive medication for OUD treatment (Meinhofer and Witman, 2018).

2.2 Medicaid and the Affordable Care Act

2.2.1 Changes in eligibility

Passed in 2010, the Patient Protection and Affordable Care Act (ACA) is a landmark United States statute that encompasses an array of reforms to healthcare service availability to the US public, which includes the income threshold and coverage group category expansion in Medicaid. Prior to the ACA, Medicaid coverage required "categorical eligibility", which generally applied to children, some of their parents, pregnant women, adults with disabilities, and some older (age 65 and up) adults. Many parents were eligible for Medicaid prior to the ACA, but income eligibility limits for parents stayed very low - typically fluctuating around 64% of the Federal Poverty Line (FPL) (Clark, 2020; KFF, 2021).

One of the most notable characteristics in the ACA expansions is the relaxation for income level eligibility for all 18–64 individuals across genders, marital statuses, and parental statuses. Individuals with income up to 138% FPL can continue coverage postpartum (via ACA expansion), effectively eliminating categorical requirements. This expansion under the ACA has reduced the proportion of pregnant women and mothers having to undergo a shift from public insurance to private insurance or from public insurance to no insurance from 50% to 30% (Clark, 2020; Daw et al., 2019). Though not comprehensive, this reduction in insurance status discontinuation, or "insurance disruption" (Daw et al., 2019), may relieve mothers of the psychological burdens heightened health risks from the period of uncertainty entailed to insurance discontinuation. Examining the relationship between Medicaid and mortality Miller et al. (2019) use longitudinal administration data from the Census Numident database and finds that there are significant decrease in overall mortality rate among adults aged 55–64 with income below 138% FPL and attained less than high school education. Specifically, in first year of expansion, the probability of annual mortality declined by 0.089 percentage points. They then find reductions of approximately 0.1 percentage points 1 year after expansion and 0.208 percentage points 2–3 years after expansion. Nevertheless, they also record an insignificant rise in mortality due to external causes. While overdose deaths are only one of the many factors, this may point to the remaining ambiguity in the relationship between Medicaid and health behaviors.

2.2.2 Health services diversification

The ACA also mandated expansion in terms under the ACA, Medicaid now includes treatment for substance use disorders (including opioid use disorder) as one of ten essential health benefits, effectively requiring insurers to offer some form of coverage for these services. Coverage for SUD treatment must be no more restrictive than coverage for other medical services to all insurers, including most Medicaid plans. Supplies and coverage for opioid agonists, especially buprenorphine and methadone have significantly risen. Especially, buprenorphine is recorded to be cost-effective (Meinhofer and Witman, 2018) and safe for pregnant and parenting women (Klaman et al., 2017).

2.2.3 Medicaid and mothers

Before the ACA Medicaid expansion in 2014, the most extensive reform in public health insurance for pregnant women was the expansion decisions in the 1980s-1990. All pregnant women with income up to 133% Federal Poverty Line became eligible for Medicaid and mothers are covered up to 60 days postpartum (MACPAC, 2018; Gifford et al., 2017). Because Medicaid is a hybrid of federal and state administration, states also had the option to offer coverage to pregnant women with varying family income levels, and thus eligibility in some states may reach 185% FPL. As of 2010, Medicaid has covered 45% of all births in the United States (Gifford et al., 2017; Daw et al., 2019; Clark, 2020; Alpert et al., 2019).

However, because pregnancy-related Medicaid did not automatically include postpartum care unless the postpartum services were included in a payment bundle that covers all health counselling, preventive care, and treatment services for prenatal, labour and delivery, and postpartum periods (MACPAC, 2018; Daw et al., 2019; Clark, 2020), many mothers face discontinuation of public insurance in the months following delivery. Daw et al. (2019) indicate that approximately 55% of pregnant women previously covered by Medicaid experience a change in insurance status (undergoing either Medicaid-uninsured or Medicaid-privately insured transition) in the postpartum period. Even though women can still continue Medicaid coverage if they qualify for parent Medicaid eligibility criteria, the substantial gap in income limit between pregnancy-related and low-income parent Medicaid would translate to the high rate of discontinuation. Specifically, as of 2013, Medicaid income limits for parents could be as low as 23% of FPL, and the median value was only 64% of FPL (KFF, 2021). For adults without disability and without children, the median Medicaid income limits shifted from 0% FPL before 2014 to 138% FPL from 2014 onward (KFF, 2021b). Figures 13a and 13b plot the distribution of states' Medicaid income limit as percentage of the FPL for parents and for pregnant women. Figure 13a indicates that after 2014, the 75^{th} quantile of Medicaid income limits across states rise substantially, yet there remain limits set at as low as 23$ FPL, indicating that the variation in eligibility and thus coverage rate across states both increase after 2014. Miller et al. (2019) report more formal results, highlighting that individuals with lower than high school education and no income from Supplemental Security Income living in an expansion state report a 49.8-percentage-point increase in Medicaid eligibility rate, a 12.8-percentage-point increase in Medicaid coverage rate, and a 4.4-percentage-point reduction in health insurance loss.

From 2014 to early 2020, 47 states had Medicaid eligibility incomes for parents beyond the federal 138% FPL minimum, reaching as high as 380% FPL in Iowa (KFF, 2021). The median income eligibility level for pregnant women's Medicaid rose to 200% FPL in 2020 (Daw et al., 2019). Because the new expansion terms essentially erased categorical eligibility, mothers with income below the threshold could continue coverage through meeting the universal income threshold. In 2013, most states except for Alabama, Idaho, Nevada, North Dakota, South Dakota, Utah, and Wyoming already maintained income limits for pregnancy-related Medicaid to be at least 150% FPL (KFF, 2021a), so Medicaid expansion under the ACA does not affect pregnancy-related Medicaid with respect to the scale of population covered.

Rather, it is the postpartum women and parents in general that saw the most pronounced change in their insurance status stability under the ACA. Indeed, in 2013, Medicaid income eligibility for parents was 105–106% in California and Colorado, 122% in Maryland, and 85% in New Mexico. However, after ACA implementation in 2014, the thresholds in all of these states reached 138% (KFF, 2021). Therefore, the income eligibility expansion from ACA does not necessarily include more pregnant women, but rather helps maintain Medicaid coverage status for a portion of mothers in their postpartum periods. Figure 15 presents states' Medicaid income limits for parents over time. The maps signify that Medicaid income limits are high among the District of Columbia, Minnesota, Connecticut, and New Jersey. In 2014, states in the West and North East generally raise their income limits, while states in the Mid-west expanded Medicaid later. Southern states tend to have the lowest income limits for parents and to either expand Medicaid later or choose not to expand. Figure 16 indicates that increase in coverage among parents, women without childre, and men without children occur predominantly in the 64–138% FPL income cohort, providing an initial confirmation that the ACA impact "near-poor" adults most substantially.

Nevertheless, there has been a scarce and mixed literature on the effect size of ACA implementation, particularly Medicaid expansion, on insurance status disruption. Even after the expansion, the proportion of insurance coverage and the weight each type of insurance assumed among the insured cohort vary across stages of pregnancy. Using data from 33 states participating in the Pregnancy Risk Assessment Monitoring System (PRAMS) from 2012 through 2014, MACPAC (2018) indicate that on average between 2012-2014, Medicaid coverd approximately 38.3% of pregnant women in prenatal care and 41.4% of deliveries. In contrast, Medicaid only covers 20.5% of all pregnant women included in the study before their pregnancy and 28.4% in postpartum period. On the other hand, the rate of private insurance coverage remained around 55-58% of all pregnant women before, during, and after their pregnancy. The change in insurance rate results in an approximately 10 percentage point decrease in insurance rate between perinatal and postpartum periods (MACPAC, 2018). In other words, at least 25% of pregnant women covered by Medicaid experienced insured-uninsured transition in their insurance status in the postpartum period. This rate is similar to the results that Daw et al. (2019) present.

Using Medicaid claims data in 2013–2015 from Colorado and Utah, Gordon et al. (2020) compare the duration of postpartum coverage among mothers prenatally Medicaid-eligible between the two adjacent states. Before the ACA, Colorado already offered pregnancy-related and parent Medicaid coverage to a wider range of income groups. Specifically, in 2013, Colorado offered Medicaid to pregnant women with income up to 185% and parents with income up to 105% of FPL while the corresponding coverage thresholds in Utah were 133% and 44%. In 2014, of the two states only Colorado adopted the Medicaid expansion terms under the ACA, thus raising the difference in eligibility income conditions for parent Medicaid coverage between the two states from a 61-percentage-point to a 94-percentage-point gap. The study highlights that all eligible women in Colorado have significantly longer coverage duration compared to Utah and mothers with severe maternal morbidity are also significantly more likely to seek outpatient services in Colorado.

There has also been evidence that such stabilizing effects may only apply to pregnant women and some categorically eligible groups. For instance, Sommers et al. (2016) assess the impact of Medicaid expansion on health insurance continuation among low-income adults among Kentucky, Texas, and Arkansas. They examine these three states because of their different decisions in 2014 with respect to ACA: Kentucky implements Medicaid expansion, Arkansas opts for the private ACA expansion path, and Texas does not adopt ACA. The study estimates that there is no significant change in disruption rate between 2013 and 2015. Kentucky does have a lower rate of experiencing uninsured period for any duration of time at 47.8% in 2015, compared to 58.4% in Arkansas and 60.4% in Texas, though the inter-state differences are statistically insignificant. However, low-income adults in Kentucky are significantly less likely to experience insurance gap of 9-11 months than those in Arkansas and Texas. Regression results also indicate that reasons of discontinuation differ across states.

2.3 ACA and the opioid crisis

Findings on the efficacy of Medicaid expansion terms on suppressing the opioid epidemic, especially among pre and post-natal women, have been complicated. Examining the health behaviors among Medicaid-covered pregnant women to evaluate the theory of "ex-ante" moral hazards associated with Medicaid, Dave et al. (2015) detect a significant association between Medicaid and smoking during pregnancy using the 1980-1990s Medicaid expansion for pregnant women as a setting. Particularly, they show that raising Medicaid eligibility by 12 percentage points increase prenatal smoking and smoking more than five cigarettes daily rates by 0.7-0.8 percentage points, signifying the existence of a moral hazard. The study further purports that the uptake of risky health behaviors may partly explain why Medicaid expansions have not been associated with substantial improvement in infant health. Albeit set in the 1980s-1990s and sampling a different targeted population, this study provides important backgrounds for how Medicaid can have unintended impacts on health behaviors among low-income individuals, especially women and parents.

Using comparative interrupted time series using retrospective Medicaid state drug utilization data from 2011 to 2014, Mahendraratnam et al. (2017) sample 8 states that expanded Medicaid in 2014 and 10 states that did not expand Medicaid through inclusion/exclusion criteria to examine the association between ACA and drug prescriptions and reimbursement. They find that one year after adoption, expansion states see a 1.4-million increase in prescription (17% increase) and a $163-million increase in reimbursement (36%) compared to non-expansion states.

Obtaining information on treatment records from the Substance Abuse and Mental Health Services Administration's (SAMHSA) Treatment Episode Data Set Admissions (TEDS-A), treatment service availability from the National Survey of Substance AbuseTreatment Services (N-SSATS), Meinhofer and Witman (2018) use a difference-in-difference model with state and time fixed effects and determine that admissions per 10,000 persons from Medicaid beneficiaries in states adopting the ACA expansion increase by 113% without crowding out spending beneficiaries of other insurance, one-third of which is offset by reduction of utilization among uninsured individuals. As a result, aggregate opioid admissions increased by 18%. Changes in utilization rate also vary across treatment services, with increases in admissions to rehabilitation centers offering MAT driving most of the increase in utilization. On the other hand, Medicaid does not seem to induce as significant changes in admissions to residential, inpatient, and detoxification settings. Finding some positive responses from the supply side, the authors confirm that the cross-service heterogeneity in utilization can be partially explained by cross-state variation in their scope of treatments covered by Medicaid. They find a 17% increase in treatment centers accepting Medicaid and a similar percentage decrease in treatment centers not accepting Medicaid, indicating that Medicaid expansion has a reallocating effect. Furthermore, they also find a substantial increase in MAT agonists availability, with aggregate gram distribution at OTPs increasing 17% and Medicaid prescriptions increasing 104%. Similarly, Wen et al. (2017) report a a pre-post increase of 1.30 prescriptions per 1000 residents per quarter in 26 early expansion states (2014 and prior), amounting to 69.7% difference in buprenorphine prescriptions per 1000 patients between the early expansion and non-expansion/late expansion states. Wen et al. (2017) also record that Medicaid buprenorphine spending per 1000 residents among early expansion states increase by $ 117.5 higher than that in late-expansion and non-expansion states. Both studies also indicate that in 2013, early expansion states already saw a somewhat higher increase in treatment admissions with MAT and buprenorphine specifically, indicating that either overdose rates had risen more rapidly right before the ACA implementation, that expectation of policy change may have spilled over, or that other coexisting and preceding policies may have been in action. Under the ACA, Medicaid expansion in service coverage and income threshold may alleviate the financial burdens and social stigma that OUD patients may face in seeking treatment.

The scope of Meinhofer and Witman (2018); Wen et al. (2017) study could not determine if the increase in utilization emerges from higher treatment rates among individuals with OUD or from an overall increase in opioid misuses and OUD cases. Furthermore, established as the linkage between Medicaid expansion under the ACA and treatments for SUD and

OUD were, the sustainability of treatment seems less conclusive. Hence, while these findings provide a promising initial expectation for Medicaid's impacts, research directly addressing the prevalence and severity of the opioid epidemic is needed. On the other hand, Olfson et al. (2018) also highlight that between 2008–2015, ACA adoption stimulated a 14 percentage point decrease in the proportion of uninsured patients among those with SUD in expansion states compared to only 6.6 percentage points among non-expansion states. However, there was no corresponding increase in treatment utilization rate among SUD patients. While this is a very early examination of Medicaid impact on treatment utilization, their results indicate that Medicaid expansion may not be able to influence the severity of the epidemic.

Focusing on three states with early Medicaid expansions in 2001–2002, Venkataramani and Chatterjee (2019) conclude that Arizona, Maine, and New York witnessed an average 3.7 deaths per 100,000 persons lower than non-expansion states, reflecting a potential protective effect of Medicaid expansion. However other studies indicate that branches of drugs may move in different currents. Examining county-level overdose mortality using the Centers for Disease Controls' National Vital Statistics System multiple-causes of deaths database, Kravitz-Wirtz et al. (2020) use the proportion of each calendar year during which a state has implemented Medicaid expansion under ACA terms as explanatory variable and report an overall fall of 6% in total opioid overdose deaths, of which heroin deaths fall by 11% and synthetic opioids deaths fall by 10% among counties in expansion states compared to non-expansion states. However, the study also identifies a 11% increase in methadone-related overdose mortality in expansion states. Because methadone is a widely used opioid agonist, these results may imply a conflicting effect from Medicaid: while more accessible treatments may allow individuals with OUD to lower the risk of mortality due to disorder-inducing substances, there is a possibility that they would instead misuse the medications used in treatment. Kravitz-Wirtz et al. (2020) findings concur with the results from Meinhofer and Witman (2018) and Wen et al. (2017), possibly highlighting improvement in access and quality of screening and diagnoses, while also potentially reflecting risks for a moral hazard associated with increased agonist availability and consumption Haight et al. (2018). However, because the mortality data that Kravitz-Wirtz et al. (2020) use does not specify if individuals have received OUD treatment or if their first access to methadone is from treatment, the potential substitution effect between agonists and addictive substances remain unclear.

Examining the impacts of different public security programs on pregnant women's health risks, Schmidt et al. (2021) conclude that social safety net generosity may have differing impacts on psychological distress levels and risky health behaviors such as daily smoking and drinking among pregnant women across types of programs offered. Specifically, a $1,000 tax benefit from the Earned Income Tax Credit (EITC) is associated with a 22.5% reduction in distress reports and a 14.2% reduction in smoking report among pregnant women. In contrast, a $1,000 benefit from the Supplemental Nutrition Assistance Program (SNAP) would increase smoking rate in the same cohort by 7.6%. On the other hand, Medicaid eligibility does not seem to significantly affect statuses of psychological distress, smoking, or drinking habits among pregnant women. While these outcome dimensions are not directly related to the opioid epidemic outcomes, the study raises questions about the impacts that sociological connotations that social safety net programs incur on beneficiaries' well-being and behaviors. Schmidt et al. (2021) posit that while the EITC benefits are granted based on working status, SNAP program may kindle "social stigma" for recipients. The same question can be raised about the social connotations that Medicaid has. Furthermore, the seeming lack of a significant relationship between Medicaid and mental well-being for prenatal women may also reflect constraints to the channels of association between Medicaid and beneficiaries' mental health and health outcomes.

Ultimately, the relationship between Medicaid and risky health behaviors, especially substance use, remain a tenuous and important field for public health research. Therefore, this paper can contribute to the existing literature on the relationship between Medicaid and substance misuse behaviors. According to Dave et al. (2015), there are three channels through which Medicaid can influence health behaviors. First, health insurance is associated with an ex ante moral hazard. Second, the income effect from public health insurance can facilitate risky consumption of drugs and other substances. Third, health insurance increases access to healthcare and medical care services, which improves on information availability. In the context of Medicaid and the ACA, increased access to substance use treatment to a larger population can help alleviate the social stigma associated with seeking mental health treatment and substance use treatment. However, accessible treatment can either incentivize individuals to adopt risky behaviors such as misusing substances (adverse effect) or raise awareness of the consequences from misusing substances (protective effects). Furthermore, improved access to standard healthcare services would also increase coverage of prescription drugs, aggravating risk of exposure to potentially addictive products.

3 Data

3.1 Intended Data

To examine the change in opioid use and outcomes in the population of interest, the suitable dataset would include information on women in their prenatal (all three trimesters) and 6 months postpartum, following the analysis by Daw et al. (2019). Among states that expanded Medicaid under ACA terms, mothers with household income between the pre-ACA threshold for parents Medicaid and the 138% FPL threshold are likely to see the most significant change in insurance continuation after 60 days following delivery date due to the ACA. Therefore, these individuals will be considered the "treatment" group. The control group would be mothers qualifying for both pregnancy-related and parent Medicaid coverage even without ACA expansion, i.e. women with very low household income.

A potential analysis could be a comparison of opioid use, misuse, and dependence between the treatment and the control groups (divided by income) within each expansion state cohort (states that expanded Medicaid before 2014, in 2014, later, and non-expansion). Because of possible systematic differences between income groups, a second comparison to examine is the change in outcome gaps across state cohorts before and after each state's Medicaid expansion year. However, because of data limitations, I will later adjust my population of interest to be parenting women.

3.2 Data

Data on the income threshold and state expansion comes from the Kaiser Family Foundation. KFF includes data on state expansion date, income threshold for adult Medicaid in terms of ratio to FPL.

Data on analgesics and heroin use in past year are retrieved from the publicly available version of the National Drug Use and Health (NSDUH) survey database. The NSDUH is the primary data source for the use of illicit drugs, prescription drugs, and substance as well as mental health status among individuals aged 12 and above. This dataset includes questions on use, misuse, and dependence in past year, age of first misuse. It also includes treatment and perceived need for treatment alongside health and societal problems due to substance misuse or dependence. The survey presents questions on demographic information such as race and ethnicity, age, gender, household composition, household and individual income thresholds, and healthcare access.

The public version of the NSDUH does not provide geographic identifiers and continuous income estimates. However, each observation is categorized into income groups of $10,000 intervals. Because the Medicaid expansion under ACA depends on both state of residence and income level, I identify exposed-unexposed group using the upper and lower bound. To get the ratio of a household's income to the FPL, I attain annual Federal Poverty Guidelines data from the Office of the Assistant Secretary for Planning and Evaluation (ASPE) report on Prior HHS Poverty Guidelines and Federal Register References. The Federal Poverty Guidelines is issued annually in the Federal Register by the Department of Health and Human Services (HHS) and this is the income guidelines used to determine if an adult qualifies for Medicaid. Because the Guidelines are constant for all states in each year, it is possible to calculate the household income ratio to determine potential exposure group. Another adjustment I make to the NSDUH data is re-scaling the analysis weights according to the data documentation from NSDUH. Particularly, to account for the 2015 redesigning, NSDUH recommended that comparison and inferences between 2002-2015 be made by dividing the original analysis weights by the number of years prior to and including 2015. Therefore, I generate a new analysis weight variable that is one-sixth of the original weight variable in 2010-2015 and then takes on the original weight assignment from 2016 onward.

Table 5 presents summary statistics for mothers aged 18–64 across income cohorts. Generally, mothers with lower incomes have larger share of Non-Hispanic Black/African American, Non-Hispanic Native American, non-Hispanic multiracial, and Hispanic than mothers with income above 138% FPL, who in turn have higher shares of non-Hispanic white and non-Hispanic Asians. Mothers with higher income are also substantially more likely to have graduated from high school, less likely to be unemployed, and more likely to live in metropolitan areas, and more likely to be married. These discrepancies confirm that lower-income mothers are more predominantly represented by individuals of color, with lower education attainment, lower job stability, and higher risks of partner absence. Due to the data structure in NSDUH, I cannot attain a point estimate of the median age in each income group. However, the interval approximation of median age still indicates that the lowest income group of mothers tend to be younger than mothers with higher income. Table 5 also indicates complicated patterns of mental health and health behavior patterns across income groups. Specifically, mothers with lower income are more likely to have misused opioid before in their life and to have experienced distress within the past year than the highest group of income. Likelihood of experiencing depression in life seems to be similar across income cohorts. Mothers in the highest income group are also more likely to have have problems with alcohol/illicit drug use problems in their lifetime and are at higher risk of heavy smoking than mothers from lower income groups. All three groups are equally likely to have had depression earlier in life.

Table 6 presents summary statistics on the changes in demographic composition and comorbidities likelihood in three groups of income before and after 2014. All three groups have statistically significant increase in the proportion of non-Hispanic white and a significant reduction in the percent of Hispanics. All three groups also see an increase in unemployment rate, lifetime opioid misuse rate, and lifetime alcohol/illicit drug use problem rate. These overall differences and shifts in demographic and comorbidity factors indicate the necessity to control for them in later analyses. Table 3 indicates that parenting women see the most substantial increase in Medicaid coverage and health insurance coverage as well as the largest decrease in recent health insurance loss. It is also important to note that because Medicaid target low-income adults aged 18–64 regardless of their marital status or gender, other groups of adults also see an increase in health coverage and a decrease in insurance loss. At the same time, however, pregnant women, whose Medicaid limits in each state are already above the 138% FPL cutoff, do not see a significant change in coverage or stability.

Finally, table 4 indicates that after 2014, all Medicaid-covered gender-parent groups experience significant increases in the likelihood of receiving Medicaid coverage for their mental health and SUD treatments. On the other hand, privately insured individuals who seek treatments do not see a significant increase in treatment coverage rate, although this is likely because private insurance already covered a large share of treatments before 2014.

To verify the results attained from the NSDUH data, I also use the Current Population Survey (CPS) attained from the Integrated Public Use Microdata Series (IPUMS) database to check how Medicaid enrollment actually changes when geographical identification is available. The CPS is a nationally representative micro-level data set that includes information on demographics, family interrelationship, employment status, health insurance status, and pregnancy status. Because the CPS collects data on past year socioeconomic statuses and locations, I select the annual data in 2011-2020. Because there is no explicit indicator for pregnancy status, I follow the method from Dave et al. (2013) to identify pregnant women as having a child aged below 1 year. I also identify gender-parent cohort by subtracting the age of the youngest child in the household and then classify parenting individuals as having children aged 17 or below, which is also the family interrelation indicator available in the NSDUH public data. A concern I have with my pregnancy status identification is that there the CPS data does not differentiate between adoptive and biological child. Therefore, I risk over-counting pregnant women.

For both data sets, I restrict my sample to parenting women aged 18–64, as this is the age group targeted by Medicaid. This is because the younger and older age groups would already qualify for other public health insurance programs such as the Children's Health Insurance

Program (CHIP) or Medicare. On the other hand, Medicaid expansion under ACA program target adults aged 18-64 by design. Therefore, restricting the age groups in my analysis allows me to more accurately identify the relationship between Medicaid expansion and the outcomes for the population that the policy target.

4 Empirical Strategies

To comprehensively understand the potential mechanism through which Medicaid may be connected to substance misuse outcomes, I follow the methodologies of Miller et al. (2019) and establish a multi-stage study. In the first stage, I will be examining the impact of Medicaid expansion on Medicaid enrollment, health insurance coverage, and insurance discontinuation among parenting women. In the second stage, I will turn to outcomes of opioid and substance use statuses among mothers. Due to the differences in data availability, I will adjust the specification strategy at each stage accordingly.

4.1 Stage one: Medicaid and healthcare coverage

Summary statistics have indicated that the wave of ACA expansion in 2014 has resulted in a significant increase in Medicaid enrollment rate, health insurance coverage rate, and similarly significant decrease in health insurance discontinuation rate. This first stage of analysis will examine the changes in insurance stability more formally with the following specification methods.

4.1.1 Outcomes

In this section, I will examine the change in likelihood of Medicaid enrollment, private insurance coverage, health insurance coverage, and insurance disruption for parenting women on both the NSDUH data. In this model, enrollment in Medicaid, private insurance, and general health insurance is defined as being covered by a specified class of health insurance. Based on the strategies used by Daw et al. (2017, 2019) and the available data in NSDUH, I define insurance discontinuation as losing health insurance within the past year. Specifically, the NSDUH asks for the last time a person has health insurance. I thus derive the disruption indicator by assigning each observation a value of 1 if the last time they had health insurance was within the past 12 months. I do not differentiate between causes of losing health insurance within the past year, which may include not feeling that they need to, and thus may miss out on the relationship Medicaid may have on the incentives for health insurance at all. However, because of the observed substantial decrease in insurance disruption among mothers compared to other gender cohorts and based on the intuition proposed by Dave et al. (2013), I argue that a parenting women is unlikely to lose health insurance because she deems it unnecessary.

Another limitation in this definition of insurance disruption is that because the NSDUH does not include specific questions on a person's change of insurance type in the past year. Therefore, I expect that the estimation I attain will differ from the actual change in "insurance churning" that Daw et al. (2017, 2019) examine. The estimation may suffer from a downward bias if parenting women are more likely to maintain their Medicaid coverage in postpartum period and thereby decreasing the rate of cross-insurance shift, provided that they are eligible. On the other hand, if the rate of cross-insurance shift increases, which is unlikely given the results by Daw et al. (2017), my estimation will suffer from an upward bias.

4.1.2 Difference-in-Difference-in-Difference approach

Research on the impact of Medicaid expansion under ACA terms have predominantly followed a difference-in-difference framework, using state's decision regarding ACA (whether to adopt or not) to identify the "treatment" group (states that adopted ACA in 2014) and counterfactual group (states that did not adopt ACA or decided to adopt ACA later in the examined timeline). I reason that this approach can still be improved on to better account for the variation in marginal change to income limits across states.

Post-ACA Medicaid requires either financial eligibility or categorical eligibility. Specifically, for adults without disability and parents, ACA-adopting states expanded Medicaid income limit to also include a "near-poor" population (with household income at or below 138%). Therefore, state population are not universally exposed to the changes in SUD treatment coverage from Medicaid. In other words, within each ACA-adopting state, only parents and adults without disability from families that financially qualify for Medicaid experience a change in treatment status, thus belonging to the "treatment" group. Furthermore, some ACA-adopting states such as Illinois (whose highest pre-ACA Medicaid income limit for parents was 191% FPL), Maine (207% FPL), Minnesota (275% FPL), New Jersey (200% FPL), New York (150% FPL), Rhode Island (192% FPL), and Vermont (192% FPL) actually reduced their Medicaid income limits to 138% FPL while including SUD treatment services to Medicaid coverage. Therefore, a portion of pre-ACA Medicaid beneficiaries may have experienced a "reverse" change in treatment status. Post-Medicaid beneficiaries in treatment states that increased their Medicaid income limits could be further categorized into two categories of exposure: those would have financially qualified for Medicaid in the absence of ACA adoption and those newly qualify. The former group would experience a change in treatment status with respect to access to SUD treatment coverage; while the latter group would experience a change in treatment status with respect to both SUD treatment access and overall insurance coverage. Thus, the proposed model would also attempt to reflect this difference in treatment status change by further dividing the income-based treatment groups into a "poor" and "near-poor" group.

Thus, to capture the effect of Medicaid expansion with state and income variation, I propose a difference-in-difference-in-difference (DDD) model that includes an internal control to state cohorts using family income level as a percentage of FPL.

$$
\begin{aligned}
Y_{istp} = {} & \beta_0 + \beta_1 \mathbf{I}_{pt}(\leq 64\% FPL) + \beta_2 \mathbf{I}_{pt}(> 64\% FPL \cap \leq 138\% FPL) + \beta_3 Post_t + \beta_4 State_s \\
& + \beta_5 State_s \times Post_t + \beta_6 \mathbf{I}_{pt}(\leq 64\% FPL) \times Post_t + \beta_7 \mathbf{I}_{pt}(> 64\% FPL \cap \leq 138\% FPL) \times Post_t \\
& + \beta_8 State_s \times \mathbf{I}_{pt}(\leq 64\% FPL) + \beta_9 State_t \times \mathbf{I}_{pt}(> 64\% FPL \cap \leq 138\% FPL) \\
& + \beta_{10} State_s \times Post_t \times \mathbf{I}_{pt}(\leq 64\% FPL) + \beta_{!1} State_s \times Post_t \times \mathbf{I}_{pt}(> 64\% FPL \cap \leq 138\% FPL) \\
& + \boldsymbol{X}_{ip} + \varepsilon_{itp} \qquad (1)
\end{aligned}
$$

Here, Y_{istp} indicates whether or not woman i residing in state s at time t belonging to income group p is covered by Medicaid, and has lost insurance in the past year. $State_s$ is a treatment-control group dummy that indicates whether the state of residence has adopted ACA. $Post_t$ indicates if the time of sampling is after ACA adoption in 2014, i.e. 2015 onward [1]. $\boldsymbol{X}_{ist}$ is the vector of individual-level controls. $\mathbf{I}_{pt}(\leq 64\%FPL)$ is the indicator that a mother has income below 64% FPL and $\mathbf{I}_{pt}(> 64\%FPL \cap \leq 138\%FPL)$ is the indicator that a mother has family income between 64–138% FPL (not including 64% FPL):

$$\mathbf{I}_{pt}(> 64\%FPL \cap \leq 138\%FPL) = \begin{cases} 1 \text{ if family income as \%FPL} \in (64, 138] \\ 0 \text{otherwise} \end{cases}$$

$$\mathbf{I}_{pt}(\leq 64\%FPL) = \begin{cases} 1 \text{ if family income as \%FPL} \in (-\infty, 64] \\ 0 \text{ otherwise} \end{cases}$$

The coefficient of interest in this model is β_{10} and β_{11}. β_{10} compare the effect of ACA adoption on Medicaid coverage rate among mothers of income below 64% FPL relative to mothers with income above 64% FPL in expansion states with the differences in ACA effect between the same cohorts in non-expansion states. β_{11} measures the same difference, but the internal treatment-control classification among expansion states is now the 64–138% FPL cohorts against the below 64% FPL and above 138%FPL cohorts combined. Expansion states are defined as states adopting Medicaid before 2014 and non-expansion states are defined as those expanding after 2014 or do not expand at all. I expect this specification to underestimate the actual effect size of ACA due to differential policy timing among ACA-adopting states.

Because the NSDUH sample does not have state identification nor a continuous point estimate of family income, I adjusted the model measuring the change in health insurance outcomes to include only income groups as defined by the national income limit before (64%

[1] I allow for one year lag from the wave of adoption in 2014 to individuals facing delays in Medicaid enrollment. Additionally, because halth insurance loss refer to last year, I also let the post period start from 2015

FPL) and after 2014 (138% FPL) as the two treatment arms. Simultaneously, although using the national median instead of state-specific income limits forgoes the cross-state variation in Medicaid eligibility rate change, the state-invariant cutoff in turn guarantees balance among treatment-control income cohorts across states. The model is set up as follows:

$$
\begin{aligned}
Y_{itp} = \beta_0 &+ \beta_1 \mathbf{I}_{pt}(\leq 64\% FPL) + \beta_2 \mathbf{I}_{pt}(> 64\% FPL \cap \leq 138\% FPL) + \beta_3 Post_t \\
&+ \beta_4 \mathbf{I}_{pt}(\leq 64\% FPL) \times Post_t + \beta_5 \mathbf{I}_{pt}(> 64\% FPL \cap \leq 138\% FPL) \times Post_t \\
&+ \boldsymbol{X}_{ip} + \varepsilon_{itp}
\end{aligned} \tag{2}
$$

The coefficients of interest are β_4 and β_5. β_4 measures the difference in change of outcome between the below-64% FPL group and the two other income groups, while β_5 measures the difference in change of outcome between the 64–138% FPL group and the two other income groups in the post-expansion period.

A limitation of this model is that because states had different Medicaid income limits before their expansion years, using the national median risks missing out on state-variant rate of Medicaid eligibility (Miller et al., 2019). For instance, a mother in Delaware in 2013 would be identified as “poor” if her household income is 120% FPL or below, and would be identified as “near poor” if her household income is greater than 120% and at or below 138% FPL (KFF, 2021). Similarly, a pregnant woman in Delaware is “poor” if her household income is at most 200% FPL and is “near poor” if her household income is above 200% and at most 214% FPL (KFF, 2021a).

4.1.3 Generalized DD with differential policy timing

Because ACA expansion did not occur simultaneously across states, nor did the percentage point change in income limit remain invariant across states, I will follow and extend on the framework of decomposition Goodman-Bacon (2018); Miller et al. (2019) propose to examine the impact of Medicaid expansion in 2010–2019 through a generalized DD model with state, time, and income group fixed effects:

$$\begin{aligned}Y_{istp} = \alpha_p + \alpha_s + \alpha_t + \beta_1^{DD} ACA_{st} \times \mathbf{I}_{pt}(\leq 64\% FPL) \\ + \beta_2^{DD} ACA_{st} \times \mathbf{I}_{pt}(> 64\% FPL \cap \leq 138\% FPL) + \boldsymbol{X}_{isp} + \varepsilon_{istp}\end{aligned} \tag{3}$$

Y_{istp} is the event that person i in state s, year t, and income group p receives Medicaid coverage or loses their health insurance. α_p is the income group fixed effect, α_s is the state fixed effect, α_t is the year fixed effect, and ACA_{st} is the indicator whether or not an individual resides in a state that has expanded Medicaid by the time they answer the survey. In this model, states are classified into groups of early and later expansion cohorts, rather than a dichotomous treatment-counterfactual group with only one time point of treatment. The coefficient of interest is β_1^{DD} and β_2^{DD}. β_1^{DD} estimates the weighted mean of all possible 3×3 difference-in-difference estimator comparing outcome changes across expansion-timing-income cohorts. In other words, when examining β_1^{DD}, at any point in time, if a person resides in a state that has not adopted ACA or has already adopted ACA in an earlier year (and thus not "varying" in its treatment status) and/or has family income above the minimum state pre-ACA income limit is treated as a member of the counterfactual group. Similarly, when examining β_2^{DD}, at any point in time, if a person resides in a state that has not adopted ACA or has already adopted ACA in an earlier year (and thus not "varying" in its treatment status) and/or has family income below the minimum state pre-ACA income limit or above the post-ACA income limit is treated as a member of the counterfactual group. On the other hand, any state varying int its expansion status assumed the role of the treatment group. Therefore, in 2011, the model would compare between states adopting ACA in 2011 with states adopting ACA in 2010, 2014, 2015, 2016, later, and states that never adopted ACA. One key assumption of this specification is the within-cohort invariability of the policy effect (Goodman-Bacon, 2018). To test this assumption, I examined the weights of $\hat{\beta}_1^{DD}$ and $\hat{\beta}_2^{DD}$ and check for robustness to treatment effect heterogeneity through time using a module de Chaisemartin and D'Haultfoeuille (2022) propose.

Given the data I have, I will first conduct a DD regression on the NSDUH sample. Then, to examine this result, I will conduct the same model as well as the event study analysis on health insurance outcomes in the CPS sample. If the two samples are comparable in their composition, I expect the DD regression to yield similar results across samples, and the event study analysis to yield a higher estimate than the DD estimate. If, however, due to differences in survey design or post-survey data organization, the two samples are not comparable, then I argue that the discrepancy between estimates attained from different specifications on the CPS sample alone could signal the degree of divergence I may attain had the event study specifications been applicable to the NSDUH sample as well.

4.2 Stage two: Medicaid and substance use outcomes

4.2.1 Outcome

To study the potential relationship between Medicaid expansion and risky health behaviors in the population of interest, I will be focusing on a mother's risk of misusing opioids and pain relievers in the past year. The reason for examining this is two-fold. First, from 2014 to 2016, the NSDUH survey underwent substantial redesigning, resulting in higher level of details for individuals' substance use behavior. Specifically, starting from the 2015 survey, interviewees were asked if they had "used" and "misused" opioid in general and narcotic products such as Tramadol, Demerol, and Codeine, which did not appear in the prior surveyed years. Therefore, estimating individual's opioid misuse in the pre-ACA years requires identifying specific opioid categories, some of which, for instance carfentanil, did not appear in the final survey before as well as after NSDUH's 2015 redesign. However, I was still able to identify more prevalent opioid products and construct a proxy indicator for past year opioid misuse. The drugs identified are listed in table 1. In figure 4, I check to see if either the opioid misuses (the "proxy") that I have identified or pain reliever misuse indicator would more closely approximate the opioid misuse cases that NSDUH survey has specified. It appears that in the 2010–2014 window, rate of misuse from opioid misuse proxy is insignificantly higher than than pain reliever misuse rate per 10,000 persons. However, in the the 2015–

2019 time window, pain reliever misuse rate is higher and gives a closer approximation to the "true" rate of opioid misuse. Overall, I reason that using both the proxy opioid misuse and pain reliever misuse indicators can provide meaningful insights into early onsets of risky health behaviors.

Figure 3(a) shows opioid misuse rate per 10,000 persons over time for men, women, and the full population. Figure 3(b) shows opioid misuse rate per 10,000 persons overtime for the full population, women, and parenting women. Although parenting women seems to have lower rate of misuse than the average misuse rate for women and for the population, the gap is closing. At the same time, however, misuse rates in both genders seem to be after 2015. Because NSDUH is asks about past-year misuse rate, I reason that the decline actually occur in 2014. Figure 4 also indicates a larger gap between the rate of substance use problems and prescription drug use problems for men and women without children than for parents and pregnant women, indicating that most cases of misuses among the latter emerge from prescription drugs. Simultaneously, the figure indicates that most of prescription drug misuse cases emerge from pain relievers, especially for parenting men and women, confirming reports from Hemsing et al. (2016). The high correlation between opioid misuse, pain reliever misuse, prescription drug misuse, and substance misuse among parenting women indicate that Medicaid can have a unique impact on substance misuse outcomes for these sub-populations.

Individuals reported a case of "misuse" if they had consumed prescription products without direct prescription from their doctors and for non-medical purposes. As a result, unlike "dependence" or "abuse", cases of misuses may not require as much formal diagnosis, thus buttressing the consistency in outcomes. Therefore, I will first examine opioid misuse, and then more general problem with use (including misuse, abuse, dependence) of pain relievers, prescription drugs, and substances (which includes alcohol, tobacco, and illicit drugs such as cocain).

4.2.2 Difference-in-difference approach

In this section, I will examine the potential relationship between the increased stability that Medicaid expansion under ACA stimulated and mothers' behavior patterns regarding substance use problems using the sample from NSDUH. As discussed earlier, the public version of the NSDUH data set provides micro-level substance use indicators and insurance statuses, but does not condone to geographical identification or imputations to attain similar classification. Therefore, following an intent-to-treat analysis framework, my approach for examining the association between Medicaid and substance misuse is through analyzing individuals' outcomes using the group of income they belong to, akin to an "as-randomized" analysis strategy in the setting of a randomized control study (RCT). Indeed, while there remain state variations in Medicaid income limits, adults with income below 138% FPL are still the target population among expansion states. Therefore, on a nation-wide scale as in the NSDUH sample, this income group can be interpreted as a "treatment" group with non-compliance (McCoy, 2017). I will continue to apply equation (2) on this study stage:

$$
\begin{aligned}
Y_{itp} &= \beta_0 + \beta_1 \mathbf{I}_{pt}(\leq 64\% FPL) + \beta_2 \mathbf{I}_{pt}(> 64\% FPL \cap \leq 138\% FPL) + \beta_3 Post_t \\
&\quad + \beta_4 \mathbf{I}_{pt}(\leq 64\% FPL) \times Post_t + \beta_5 \mathbf{I}_{pt}(> 64\% FPL \cap \leq 138\% FPL) \times Post_t \\
&\quad + \boldsymbol{X}_{itp} + \boldsymbol{C}_{itp} + \varepsilon_{itp}
\end{aligned} \tag{4}
$$

Y_{itp} denotes the event that a woman i in year t and income group p misused opioids in the past year.[2] $\boldsymbol{C}_{itp}$ denotes the presence of comorbidities and drug education, which include the event that a woman has had any lifetime alcohol/illicit drug use problems, has misused opioids before, has experienced distress in the past year or depression, and has received education on drug use in school or at work in lifetime. The coefficients of interest are β_4 and β_5. Specifically, the coefficient associated with the interaction between the indicator for having family income below 64% FPL, β_4, compares the change in misuse percentage of a woman being classified as poor enough for Medicaid before ACA expansion against

[2] Because the survey refers to drug misuse in the past 12 months, I let assign post-treatment period to years 2015 onward.

the change in misuse percentage of a woman with income above 64% FPL. The coefficient associated with the interaction between the indicator for having family income from 64-138% FPL, β_5, compare the change in misuse percentage of a woman eligible for Medicaid only after ACA adoption against the change in misuse percentage of a woman with income below 64% FPL or above 138% FPL.

Because this research design resembles that of a multi-arm clinical trial, with the below-64% FPL cohort being the low-intensity and the 64–138% FPL being the high-intensity treatment groups, to better gauge the effect size on each cohort compared to the above-138% FPL cohort–the "control" group, after conducting regression (4), I restrict the sample to only include either the below-64% FPL and above-138% FPL cohorts or the 64–138% FPL and above-138% FPL cohorts. The additional regressions are:

$$Y_{itp} = \beta_0 + \beta_1 \mathbf{I}_{pt}(\leq 64\% FPL)) + \beta_2 Post_t + \beta_3 \mathbf{I}_{pt}(\leq 64\% FPL) \times Post_t + \boldsymbol{X}_{ip} + \boldsymbol{C}_{ip} + \varepsilon_{itp} \tag{5}$$

$$\begin{aligned} Y_{itp} = {} & \beta_0 + \beta_1 \mathbf{I}_{pt}(> 64\% FPL \cap \leq 138\% FPL) + \beta_2 Post_t + \beta_3 \mathbf{I}_{pt}(> 64\% FPL \cap \leq 138\% FPL) \times Post_t \\ & + \boldsymbol{X}_{ip} + \boldsymbol{C}_{ip} + \varepsilon_{itp} \end{aligned} \tag{6}$$

In equation (5), the coefficient of interest is β_3, which measures the distance in the rate of change to opioid misuses between mothers with income below 64% and mothers with income above 138% FPL. In equation (6), the coefficient of interest is β_3, which measures the distance in the rate of change to opioid misuses between mothers with income 64–138% and mothers with income above 138% FPL.

5 Results

5.1 Insurance coverage

Table 7 reports the results for regression (2) using the NSDUH sample and table 9 reports the results for regression (2) using the CPS sample. In table 7, column (1) indicates that before 2014, coverage rate for mothers with income below 64% FPL is by 41 percentage point higher than coverage rate for those incomes above 64% FPL, on average. Coverage rate for mothers with income 64–138% FPL is 27.1 percentage points higher than mothers whose incomes are outside of this range on average. After 2014, poor mothers generally experience a 5-percentage-point increase in Medicaid coverage compared to mothers with income above 64% FPL, a 22.8% increase; while near-poor mothers see a 12-percentage-point increase in Medicaid coverage growth compared to the other two cohorts combined on average, a 54.8% increase. In column (2), after controlling for demographic characteristics, the coefficients for both income cohorts do not significantly change.

In table 9, the results indicate lower coefficients for both income groups. Specifically, both columns 1 and 2 indicate that poor mothers experience a significant and substantial increase in Medicaid coverage rate of 4.19 (without demographics controls, a 24.6% increase) and 3.91 percentage points (with demographics controls, a 23.9% increase) after 2014, compared to mothers from the other two income groups combined. Mothers with near-poor incomes also only experience a 8.13 (without demographics controls, a 47.8% increase) and 8.15 percentage point (with demographics controls, a 47.9% increase) increase in coverage rate compared to other income groups. The magnitude of coefficients on both income cohorts mothers, as well as the percentage of increase for near-poor mothers' Medicaid coverage rate from the NSDUH sample estimation are higher. However, the percentage increase in coverage rate for poor mothers is higher in the CPS sample estimation.

Table 10 presents results for regression (1) and reports a substantially lower coverage growth among near-poor mothers of 5.01 percentage points when demographics controls are not included and 4.87 percentage points when demographics controls are included. The regression results after excluding early-expansion states still indicate a significant but low growth increase among near-poor mothers compared to other cohort. Based on figure 14, this result indicates that by not considering differential timing, I am underestimating the true effect size of ACA expansion on Medicaid coverage. Therefore, I alternatively employed the generalized DD framework with fixed effects for income, state, and year. The gains in Medicaid coverage growth for low-income mothers continue to decrease after excluding early-expansion states, as reported in table 11.

Finally, presenting the results for regression (3), table 12 generally reports a higher increase in coverage growth rate for both treatment cohorts. Column (1) indicates that in any year, a mother with low income residing in a state that has expanded Medicaid has a 10.8-percentage-point increase in Medicaid coverage rate among poor mothers, a 63.5% increase. Mothers with near-poor income experience a 17.7-percentage-point increase in coverage rate, a 104.1% increase. Column (2) reports that when demographic characteristics are controlled for, coverage rate among poor mothers now increases by 10.4 percentage points (a 61.2% rise). While the absolute value of growth appreciation for near-poor mothers are still lower than the estimation from NSDUH sample, percentage of increase in coverage has increased substantially in the generalized DD estimation. Furthermore, the coefficients for poor mothers in the twoway fixed effect estimation is now substantially higher than the estimation from NSDUH sample. These results are expected because the NSDUH sample specification misses out on state's variation in pre-ACA Medicaid limits. I also expect the rise in Medicaid coverage to further increase if the two treatment groups are defined based on states' pre-ACA Medicaid income limit rather than the national median pre-2014 Medicaid income limit.

The results from equation (3) also calls for more robustness checks, including examining the heterogeneity in effect through time among expansion states. Miller et al. (2019) use the decomposition method from Goodman-Bacon (2018) to examine this source of bias and have detected that their findings on Medicaid coverage increase for low-income adults are robust. The effects might change for a different population (parenting women aged 18–64 in this study), but implementing the decomposition is beyond the scope of this study. The results from equation (3) is meant to show how much of the true effect between the ACA and Medicaid coverage are understated due to missing crucial state identifications.

However, the NSDUH sample still somewhat captures the increase in Medicaid coverage using income groups as treatment-control classification. One possible explanation for proximity is the shift in treatment-control status composition among mothers. Indeed, figure 17 indicates that after 2014, the majority of mothers from all income cohorts reside in states that have expanded Medicaid. This confirms the fact that in 2014, 26 states (50.2% of all US states) have adopted ACA. Therefore, nation-wide estimation of Medicaid coverage growth after 2014 as attained from the NSDUH sample still gives a close answer to when state controls are available. However, the inconsistency in coverage growth for poor mothers across specifications signifies the importance of cross-state variation in pre-ACA Medicaid eligibility proportions.

Finally, table 8 indicates that low-income mothers experience a substantial and significant reduction in insurance loss, with discontinuation rate reducing by 1.52 percentage points (a 36.5% reduction) among poor mothers; and by 2.57 percentage points (a 62.7% reduction) among near-poor mothers. Because the CPS does not provide information on health insurance losses or changes, I cannot verify these results. However, based on the findings for Medicaid coverage rate, I reason that the relationship between Medicaid expansion and health insurance loss among mothers as estimated from the NSDUH sample is likely to understate the real reduction in insurance discontinuation.

Based on these results, I argue that while there are differences in results, the NSDUH sample still provides a reasonable classification of treatment-control groups for examining the relationship between Medicaid and substance misuse outcomes in the next stage of this study.

5.2 Substance misuse

Table 13 presents results for equation (4). While column (1) (without demographics and comorbidity controls) and 2 (with only demographic controls) report insignificant changes for both treatment groups of mothers; column (3) (with demographic and comorbidities controls) indicate that opioid misuse rate among poor mothers decreases by 2.94 percentage point after 2014 compared to mothers with income above 64% FPL, a 76% reduction on average. Without controls for demographics and comorbidities, columns (1) and (2) indicate an insignificant decrease in opioid misuse among 64–138% FPL mothers, implying no significant relationship betwee Medicaid and opioid misuse. However, column (3) reports that misuse rate among near-poor mothers on average decreases by 1.95 percentage point compared to mothers with income below 64% or above 138% FPL on average, holding demographics and comorbidities statuses constant. This result is significant at $\alpha = 0.01$ and constitutes a 50.9% decrease. Table 14 presents results for regression (5), where column (1) reports on regression results without demographics and comorbidities controls, column (2) reports on regression results with only demographics controls, and column (3) reports on regression results with demographics and comorbidities controls. This pair-wise comparison indicates that there when comorbidities and demographics are accounted for, belonging to the non-poor group is associated with a 2.78 percentage point decrease in opioid misuse, a 74.33% reduction. Table 15 presents results for regression (5), where column (1) reports on regression results without demographics and comorbidities controls, column (2) reports on regression results with only demographics controls, and column (3) reports on regression results with demographics and comorbidities controls. This second pair-wise comparison indicates that there when comorbidities and demographics are accounted for, being in a near-poor group is associated with a 1.61 percentage point reduction in misuse compared to non-poor mothers, a 42% reduction. Generally, these two results are not significantly different from the multi-treatment arm DD regression in table 13, indicating that the difference between below-64% and above 138% FPL groups explains for most of the difference between the former and above-64% income groups combined. Similarly, the difference between 64–138% and above 138% FPL groups explains for most of the difference between the former and two remaining income groups combined 13.

Table 16 reports the results for regression (4) with pain reliever use problem, prescription drug use problem, and substance use problem as outcomes, controlling for demographics and comorbidities. Column (1) indicates that the rate of pain reliever problems among poor mothers reduces by 4.04 percentage points compared to above-64% FPL mothers, a 96.2% decrease; and that the rate of pain reliever problems among near-poor mothers decrease by

2.41 percentage points, a 57.4% reduction. Column (2) indicates that prescription drug use among poor mothers decreases by 4.61 percentage points, a 77.7% reduction, and that among near-poor mothers decreases by 2.8 percentage points, a 46.7% reduction. Finally column (3) indicates that substance use among poor mothers decreases by 3.88 percentage points, a 0.26% reduction, and that among near-poor mothers reduce by 2.43 percentage points, a 0.16% reduction. Although the coefficients for both income groups of interest increase in magnitude when the outcome is substance use problems, the effect size of Medicaid on this outcome is small (ranging only around 0.2–0.3% reduction). One interpretation for this reduction in percentage decrease is that Medicaid may not impact non-prescription drugs as substantially as it does with prescription drugs.

Because the misuse trend in each income group before 2014 is nonlinear, I replicate regression (4) while restricting the sampled years to 2013–2019, including only one pre-ACA period. Table 17 presents the results for regression (4) with only 2013 as the pre-treament year, where column (1) reports on regression results without demographics and comorbidities controls, column (2) reports on regression results with only demographics controls, and column (3) reports on regression results with demographics and comorbidities controls. Table 18 reports the results for regression (4) with pain reliever misuses, prescription drug misuses, and substance misuses as outcomes, controlling for demographics and comorbidities. Both tables indicate that the reductions in substance misuse rates remain significant for poor mothers. Indeed, while column (2) in table 17 indicate the absence of a significant association between Medicaid and opioid misuse, column (3) indicates that after 2014 opioid misuse rate among poor mothers reduces by 6.06 percentage points from their 2013 misuse average rates percentage points compared to other income groups. Table 18 reports that their pain reliever use problem rate decreases by 6.88 percentage points, prescription drug misuse by 8.38 percentage points, and substance use by 7.75 percentage points on average, controlling for demographics and comorbidities. Column (3) from table 17 also reports a significant reduction of 3.04 percentage points among near-poor mothers compared to poor and non-poor mothers combined, representing a 80.4% reduction. Table 18 indicates that Medicaid coverage growth among near-poor mothers does not have a significant relationship with rate of pain reliever use problems, as indicated in column (1). However, columns (2) and (3) indicate that there are significant decreases in the likelihood of having prescription drug problems and substance use problems: prescription drug problem rate decreases by 2.2 percentage points, a 32.97% reduction; and substance use problem rate decreases by 2.72 percentage points, a 0.17% reduction.

In both the full sample and restricted-year sample, the coefficients associated with the near-poor group in restricted sampled years are larger in magnitude to those in the full sample when demographics, comorbidities, and social education are controlled for. Simultaneously, the coefficient for near-poor mothers tend to change sign when comorbidities and demographics are controlled for, indicating that demographics, comorbidities, and social education are important factors.

Overall, the coefficients for interaction between belonging to a below-64% FPL group or a 64–138% FPL group with post 2014 are negative and statistically significant when demographics, comorbidities, and social education are controlled for. These results may hence signal a potentially protective effect from Medicaid expansion on drug misuses and abuses among parenting women. However, the magnitude of effect size may indicate that Medicaid is also unlikely to be the sole determinant of health behaviors among women. The fact that the coefficients on poor mothers, who experience increased access to treatment, are larger than those for near-poor mothers, who experience both increased coverage and access to treatment, signifies there may be a need to control for more factors. Another explanation is that because the rate of misuse among poor mothers is already higher, the percentage points of decrease would be larger for this group.

6 Robustness check

Several concerns arise with this study, especially when longitudinal data is unavailable and, within the context of this paper, clear treatment-control classification (i.e. geographical identification) is not available. First, there are concerns of endogeneity, where individuals with pre-existing substance use issue would enroll in Medicaid because they expect to receive coverage for treatment, or states expand Medicaid and SUD treatments as a response to surging overdose mortality.

6.1 Common trend assumption test

While I do not have longitudinal data on individual's substance misuse, I reason that by testing for the validity of the pre-treatment parallel trend assumption, reliable inferences can still be made on the existence of endogeneity. If the treatment and control groups do not already have different outcomes before 2014, then by assigning a placebo "post" to any year before 2014, I should not get a statistically significant coefficient on the interaction between a treatment group and the post time.

To test the parallel line assumption and to better evaluate the effect size of Medicaid expansion on substance misuse, and to verify the validity of a causal inference, I replicate regression (5) and (6) on the pre-ACA years from 2010–2013, as reported in table 19, controlling for demographics, comorbidities, and drug education[3]. In panel (a), before 2014, poor mothers have accelerating opioid misuse rate compared to mothers from control group, while near-poor mothers seem to have decreasing opioid misuse rate compared to the control group. However, the results indicate that there are generally no significant difference between each treatment group and the control group in terms of opioid misuse, except for the significant increase in poor mothers' opioid misuse in period 2012–2014. Panel (d) indicates that near-poor mothers already have accelerating Medicaid coverage compared to non-poor mothers, and the difference in coverage growth is significant in 2010–2012 window. Panels (b), (c), and (e) indicate that there is no significant difference in changes for prescription drugs use problem, substances use problem, and health insurance loss rate before 2014.

To evaluate if there exists a real effect from Medicaid expansion, I compared the effect sizes reported from table 14 and table 15 and the pre-treatment effect differences with false

[3]comorbidities and drug education are included in regression for misuse outcomes only

treatment events in figure 18, 19, and 20. Panel (a) in presents the coefficient estimates of *Below* 64% $FPL \times Post$ in both the full sample and the restricted-year sample (2014–2019); the placebo *Below* 64% $FPL \times Post(false)$ in each pre-treatment windows 2010–2012 (with placebo policy year assigned to 2011), 2011–2013 (with placebo policy year assigned to 2012), 2012–2014 (with placebo policy year assigned to 2013). Similarly, panel (b) compares the estimates of $64 - 138\%$ $FPL \times Post$ and the placebo $64 - 138\%$ $FPL \times Post(false)$.

Figure 18 reports that the coefficients for both the poor and near-poor groups interacting with the true post period on Medicaid coverage are positive and large in magnitude compared to placebo coefficients, although the 95% CIs still indicate that there are overlaps. Figure 19 indicates that the coefficients, while significant, do not lie outside of the placebo coefficient distribution. Furthermore, it seems that insurance loss already follows an inconsistent pattern before 2014. Therefore, I argue that Medicaid may be associated with a reduction in health insurance loss among low-income mothers, but causality and effect size have not been established.

Figure 20 indicates that the point estimate of the coefficients are negative and larger in magnitude compared to placebo coefficients, there remain overap in 95% CI, especially for near-poor mothers. The significant placebo coefficient for poor mothers in 2012–2014 window is a concern, but this could be due to recall bias in survey, outliers. Lacking state-level policy controls such as drug triplicate program, PDMP, and third-party Naloxone access (Alpert et al., 2019), validity of the common trend assumption and the true effect sizes may differ.

6.2 Placebo test

Another concern in this study is that Medicaid coverage increase among low-income mothers is absorbing relevant factors that are unaccounted for. This concern is especially prominent in the context of this study, given the lack of geographical identification and thus controls for regulations and policies. To address this concern, I adopt the robustness-checking strategy from Miller et al. (2019) and run a placebo test on substance misuses among women aged 65-138% FPL as an alternative population that is not targeted by Medicaid, following the robustness check strategy in Miller et al. (2019). I confirm that ACA does not affect Medicaid coverage growth in this age demographic by applying regression equation (3) for Medicaid coverage outcomes in this alternative demographic. Column (1) from table 20 indicates that the below-64% FPL women group did not see a significant change in Medicaid coverage growth compared to above-64% FPL women group. Similarly, the 64–138% FPL group did not see a significant change in Medicaid coverage growth compared to the other income groups combined. I then apply regression equation (4) to examine the relationship between ACA expansion and opioid misuse, problems with pain reliever, with prescription drugs, and with substances among women aged 65 and above. The results in columns (2)–(5) in table 20 indicate that while below-64% FPL older women do not see a significant difference in changes to substance use problems after 2014 compared to the above 64% FPL groups, the 64–138% FPL group sees a significant reduction in substance use growth after 2014 compared to the other two income groups combined. Nevertheless, the near-poor group's rate of change in opioids, pain relievers, and general prescription drugs are insignificant and substantially lower in magnitude compared to their 18–64% FPL counterparts. However, these insignificant results may emerge from the very low rate of prescription drugs use problems among those aged above 65, as indicated by the overall rate for opioid, pain reliever, and prescription drugs misuse/abuse/dependence reported as the means of outcome variables in table 20. Therefore, while prescription drugs misuses may be influenced by Medicaid expansion, unobserved factors may have influenced substance misuses - which includes alcohol, tobacco, and illicit drugs.

7 Limitations

Due to the data confidentiality measures taken by the NSDUH, I was not able to precisely identify the treatment and counterfactual groups using geographical identification. Therefore, my analysis must rely on an intent to study framework that risks underestimating the actual effect size. Additionally, because states had different pre-ACA Medicaid income limits for pregnant women, parents, and adults, my analysis also misses out on the cross-state income limits. On the other hand, variation in income limits would entail variation in internal control group's size, creating an imbalance across states. Another concern with using income groups as the treatment-counterfactual identification means I am comparing between cohorts of different socioeconomic backgrounds. Therefore, this analysis cannot secure the exchangeability between the treatment-control observations, rendering causal inference even more tenuous.

Furthermore, because of the 2015 redesign in the NSDUH questions, there remain concerns for data inconsistency before and after 2015. Particularly, because the NSDUH did not include opioid misuse as a question before 2015, I instead identified cases of opioid misuse by selecting any indication of misuse for a product that has opiate components. Comparing between the constructed and the original indicator of opioid misuse in the 2015-2019 period shows that my constructed opioid misuse identifier underestimates the cases of actual misuse, though by a small margin and the trends remain consistent with NSUDH's record.

Another limitation in this study is that I could not distinguish postpartum women from general parenting women. Therefore, it remains unclear whether the decrease in insurance loss comes predominantly from new mothers or if there are similar patterns across both cohorts. According to Daw et al. (2017, 2019) parenting women are particularly vulnerable to health insurance disruption either through insurance loss or insurance switch. Additionally, health behaviors among parenting women may vary with child's age.

By using income groups as controls, I cannot avoid demographic differences among treatment-comparison cohorts. Because the data from the NSDUH is cross-sectional, my analyses may also suffer from bias when there exist demographics changes in each control-treatment cohorts. Simultaneously, unaccounted-for confounders remain a concern. Past research from Meinhofer and Witman (2018); Miller et al. (2019); Kravitz-Wirtz et al. (2020); Alpert et al. (2019) indicate that state regulations on opioids such as the triplicate program, prescription drug monitoring program (PDMP), opioid supply rate, marijuana legalization, among others, and Medicare part D launch status, may all influence the misuse patterns for opioids.

Focusing on substance misuse/abuse/dependence behaviors among parenting women, I have not explored other important indicators to understand the severity of the opioid epidemic, including non-fatal overdose, overdose mortality, or repeated use and relapsing. These are all crucial dimensions to examine in future studies. I have also not examined other demographic groups, who may have different misuse patterns or sources of misuse. For instance, there is evidence that women are more likely to misuse prescription drugs attained from doctors, friends and relatives, or acquaintances than men (Hemsing et al., 2016). This difference indicate a need for studies on gender and age-specific treatment and coverage policies in future research. Finally, this study does not specifically look at misuse rate for specific opioids, whose prominence in the opioid epidemic over the years according to past literature (CDC, 2021; Kravitz-Wirtz et al., 2020; Wen et al., 2017). My analyses also do not look at the number of substances misused, or if there are repeated misuses. An avenue for future research on the opioid crisis could be on the potential complementary/substitute effects among opiate drugs.

8 Discussion

The contribution of this paper to the existing literature is two-fold. First, my study is suggestive of a zero to negative association between Medicaid and opioid misuse among parenting women, providing a motivation for causal analyses in the future.The results on opioid and substance misuse in this analysis are consistent with the findings from Kravitz-Wirtz et al. (2020) and Miller et al. (2019) that Medicaid expansion may potentially have a protective impact on health behaviors. While likely understating the real replationship between Medicaid and opioid misuses, the negative and statistically significant results both signify that there is an association between increased insurance coverage, stability, and access to treatment that Medicaid offers under the ACA. While this study does not confirm that moral hazards are not applicable to substance use disorder, or that there is a causal relationship between Medicaid and drug misuse, it is suggestive that Medicaid and the ACA have a negative association with opioid misuse among parenting women. One explanation for this possibility is that the increased access to health insurance alongside treatment, the reduction in insurance loss, and the attempt to lower social stigmas regarding SUD and mental health treatments that the ACA may have an "information" effect. My study is thus an addition to the existing literature on the moral hazards from public health insurance and potential solutions to the opioid epidemic. Furthermore, my results can be a basis for policy makers that availability of safety net can also have a positive impact on health behaviors.

Second, my study results are consistent with Daw et al. (2017) that the ACA results in a sizeable increase in insurance coverage and decrease in discontinuation for low-income parenting women. The results on Medicaid coverage as well as health insurance loss among low income mothers aged 18–64, a subgroup of the targeted population for Medicaid, signify that Medicaid expansion under the ACA can produce a meaningful protective impact for low-income mothers in terms of health insurance stability. Using alternative estimation strategies, I provide initial motivations to argue that expanding Medicaid under the ACA may most substantially affect mothers with "near-poor" family incomes (above pre-ACA income limits but below 138% FPL). Although I am examining a different cohort, these results are consistent with findings from Daw et al. (2017, 2019); Miller et al. (2019). Nevertheless, because insurance disruption among low-income adults, especially mothers, remain high, my finding indicate that Medicaid can be an important channel for increasing health insurance coverage and reducing income shock due to sickness and medical care spending, echoing the point that Einav and Finkelstein (2017); Daw et al. (2017) posit.

Health insurance remains an important tool for a creating social safety net; increased access to prescription medications are a crucial avenue for reducing catastrophic health events, thereby improving health as well as economic outcomes for low-income individuals. While restricting drug supply is not necessarily a policy goal (Saloner et al., 2022), opioids, prescription drugs, and substance misuse as well as overdose remain a concerning problem in the US. Different demographic and socioeconomic groups face heterogeneous barriers to treatment and consequences. Therefore, regulations on prescriptions and implementations of demographic-specific treatment programs remain an important task. The increase in health insurance coverage and reduction in insurance disruption can create much-needed financial stability, increase chances of survival, while necessitating mental health and SUD treatments can reduce the social stigma against these services. Examination of these manifold mechanisms can pose a helpful tool in alleviating this epidemic.

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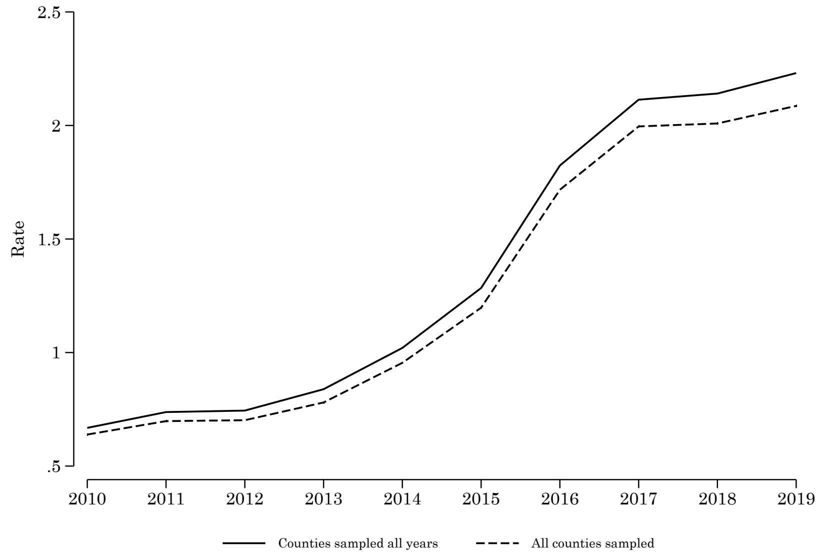
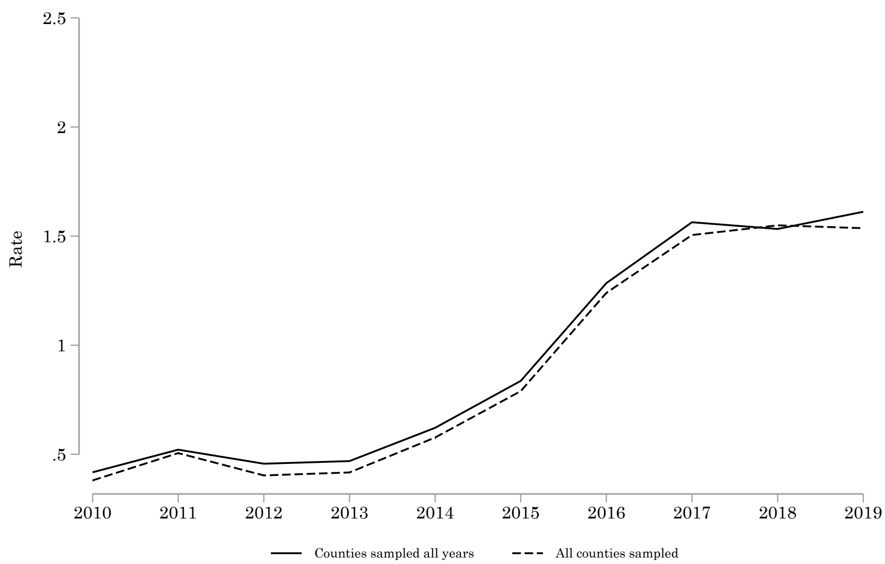
9 Figures and tables

Figure 2: National deaths due to opioids per 10000 populations

(a) National record



(b) Women aged 15-49



This figure shows the change in rate of opioid overdose deaths per 10,000 in 2010–2019, with a trend for counties reporting in all years sampled and one trend for all counties included in the dataset. Data source: CDC WONDER Multiple Cause of Death Database.

Figure 3: Opioid misuse rates

(a) Opioid misuse total population

(b) Opioid misuse among parenting women

Figure 4: Opioid and others substances misuses per 10,000 persons by gender-parent group

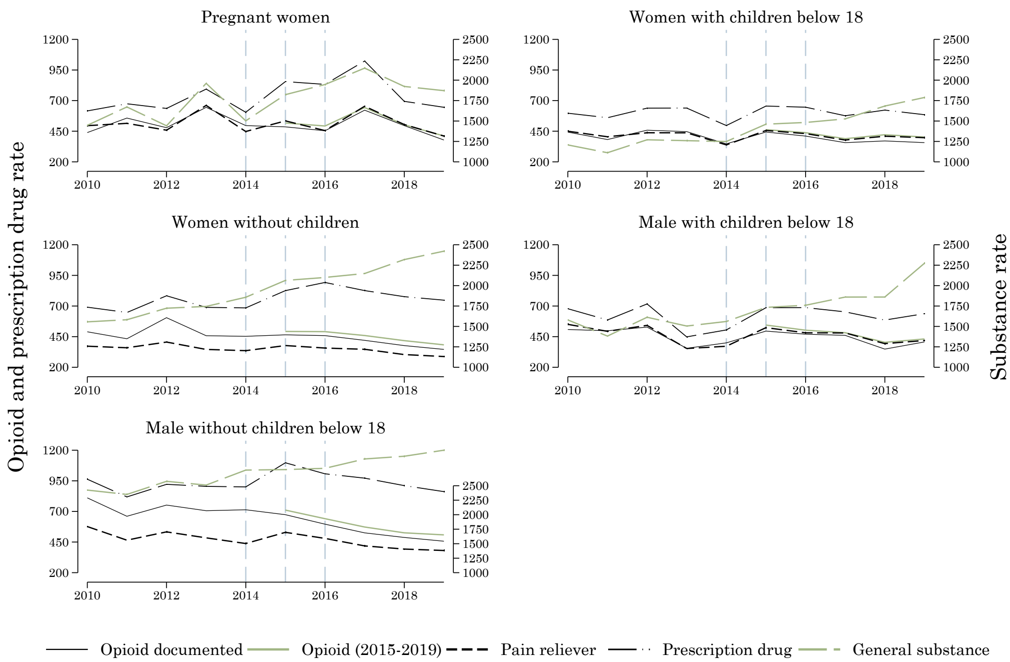
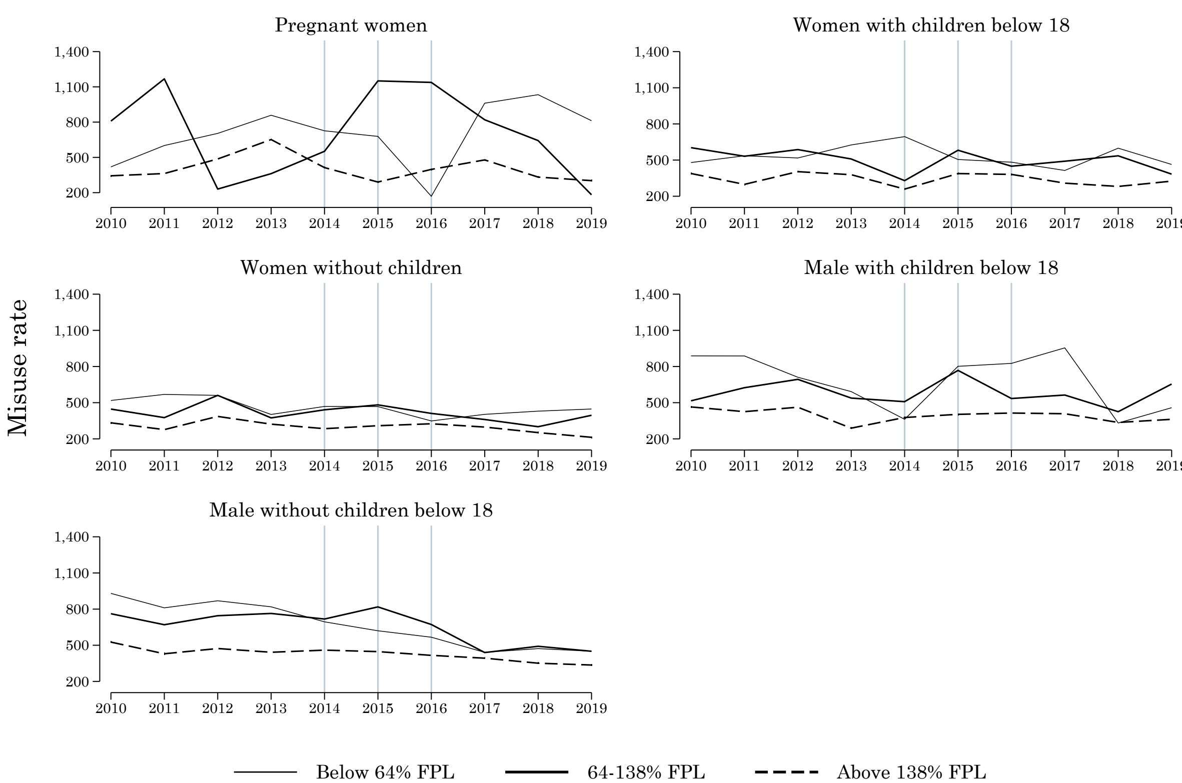


Figure 5: Opioid misuses per 10,000 persons by gender-parent and income groups



Data source: NSDUH

Table 1: Opioid identified in NSDUH

Ingredient	Brand name
Oxycodone	Vicodin, OxyContin
Fentanyl	
Oxymorphone	
Meredipine	Demerol
Tramadol	Ultram, Ultram ER, Conzip
Hydrocodone	
Hydromorphone	
Opium	
Pentazocine	Talwin
Methadone	
Buprenorphine	
Morphine	
Codeine	
Butorphanol	Stadol

This table reports the names of opioids ingredients and brands that are mentioned in NSDUH questions in years 2010–2019.

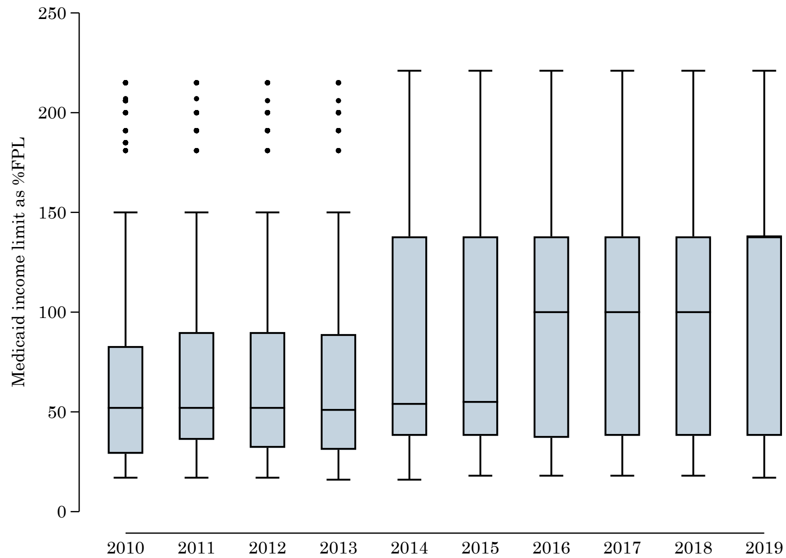
Table 2: Opioid identified in NSDUH

Covariates	Outcomes
Demographics and socioeconomic controls	
Being non-Hispanic white	Medicaid coverage, insurance loss, opioid misuses, pain reliever problems, prescription drugs problems, substance problems
Graduated from high school	Medicaid coverage, insurance loss, opioid misuses, pain reliever problems, prescription drugs problems, substance problems
Is unemployed	Medicaid coverage, insurance loss, opioid misuses, pain reliever problems, prescription drugs problems, substance problems
Residing in metropolitan area	Medicaid coverage, insurance loss, opioid misuses, pain reliever problems, prescription drugs problems, substance problems
Age (fixed effects)	Medicaid coverage, insurance loss, opioid misuses, pain reliever problems, prescription drugs problems, substance problems
Is married	Medicaid coverage, insurance loss, opioid misuses, pain reliever problems, prescription drugs problems, substance problems
Comorbidities controls	
Used opioids before	Opioid misuses, pain reliever problems prescription drugs problems, substance problems
Had problems with alcohol/illicit drugs use before	Opioid misuses, pain reliever problems prescription drugs problems, substance problems
At high risk of heavy smoking	Opioid misuses, pain reliever problems prescription drugs problems, substance problems
Had depression in lifetime	Opioid misuses, pain reliever problems prescription drugs problems, substance problems
Experienced distress in past year	Opioid misuses, pain reliever problems prescription drugs problems, substance problems
Education on drugs	
Received any education on drugs and mental health service at school or work	Opioid misuses, pain reliever problems prescription drugs problems, substance problems

This table lists the covariates used in the two stages of this study.

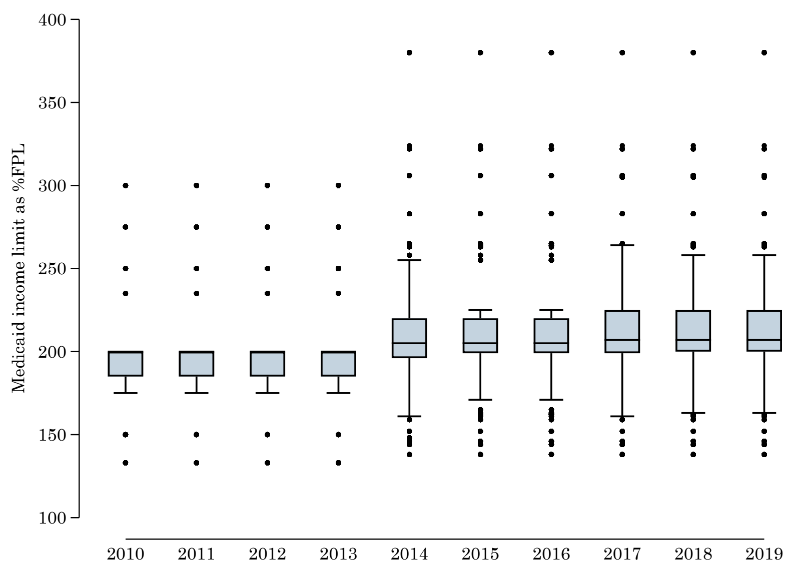
Figure 13: Medicaid income limits 2010-2019

(a) For parents



Source: KFF (2021)

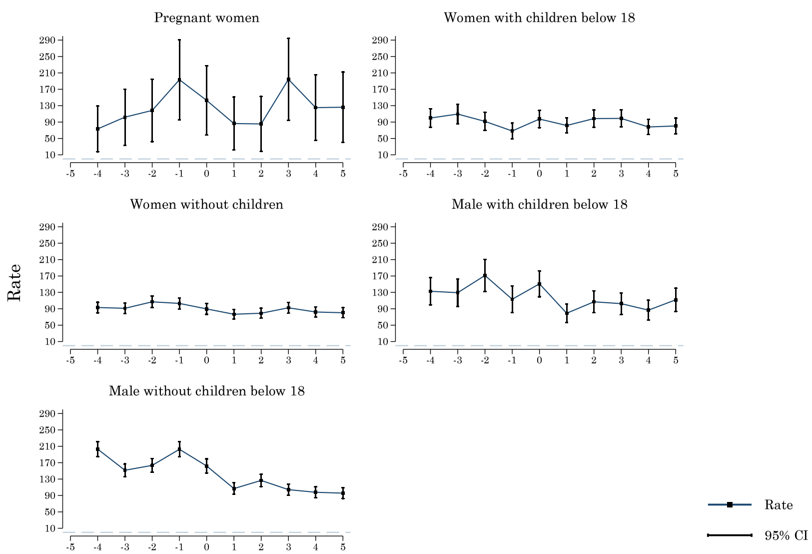
(b) For pregnant women



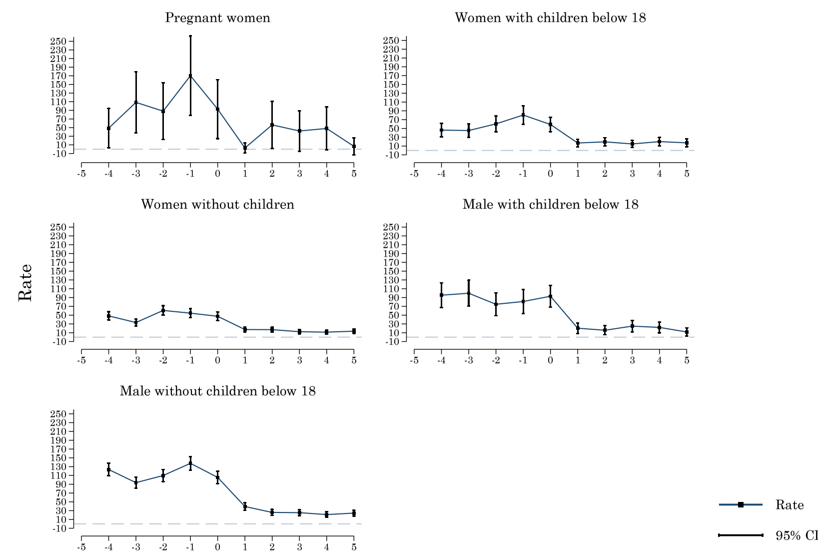
Source: KFF (2021a)

Figure 6: Natural opioids misuses per 10,000 persons

(a) Codeine



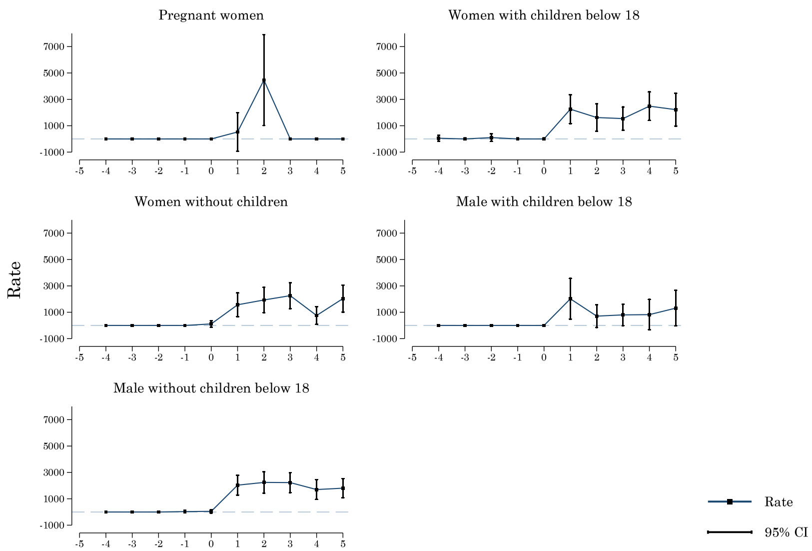
(b) Morphine



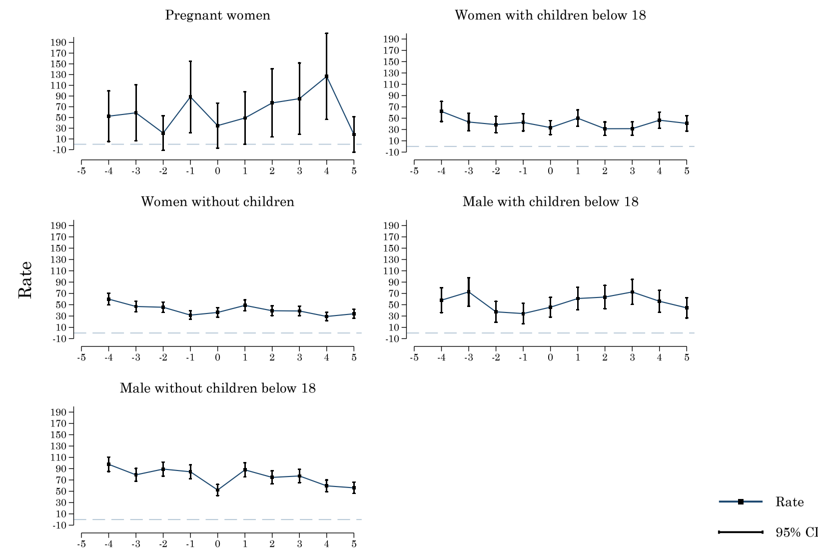
Source: NSDUH

Figure 7: Semi-synthetic opioids misuses per 10,000 persons (I)

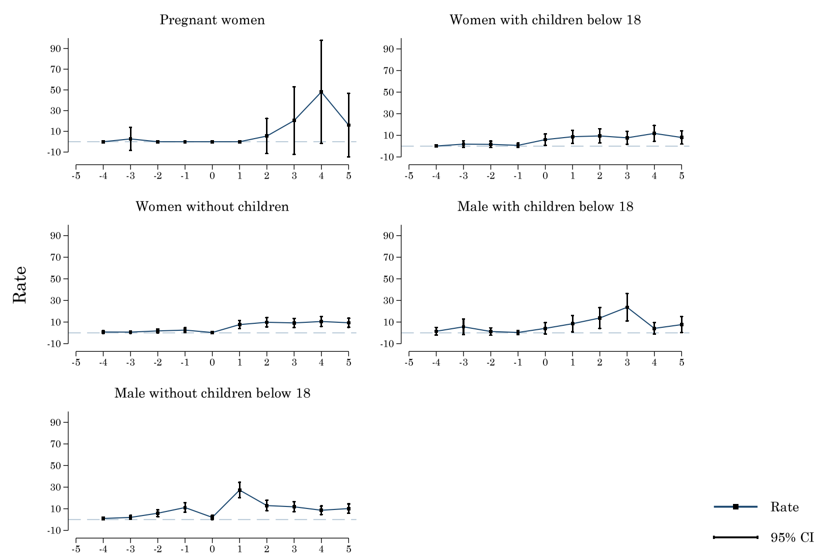
(a) Heroin



(b) OxyContin



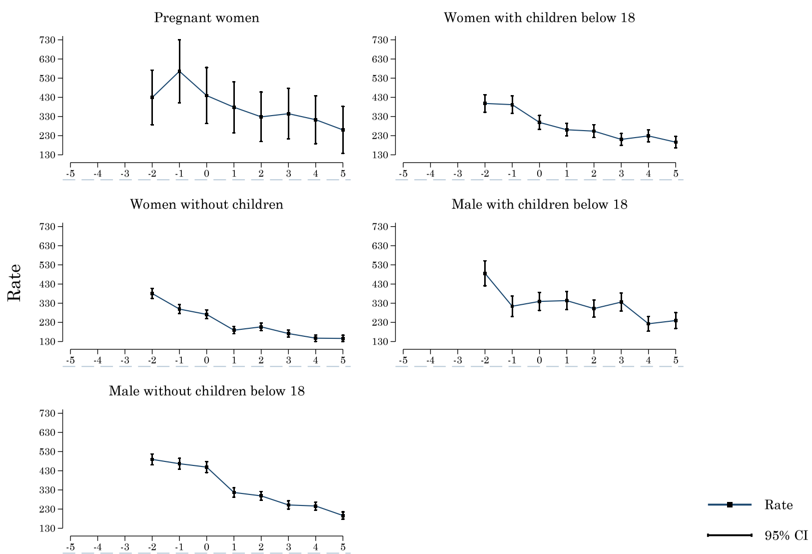
(c) Oxymorphone



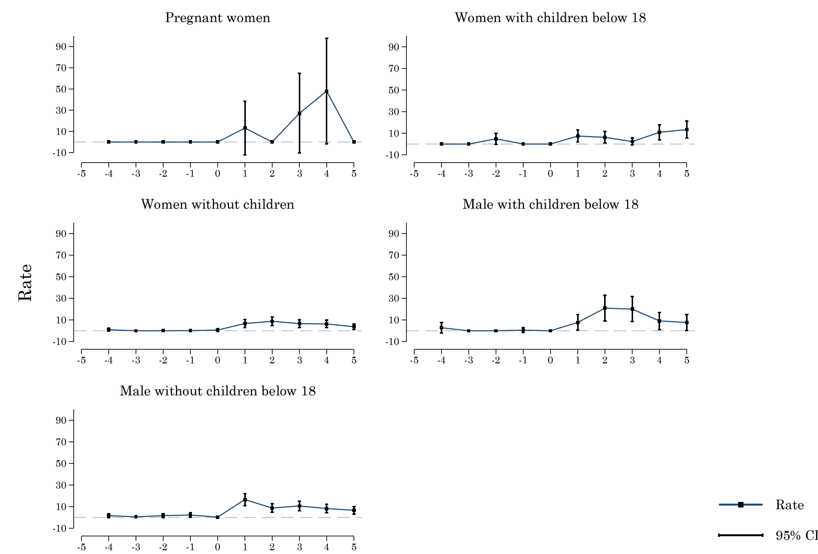
Source: NSDUH

Figure 8: Semi-synthetic opioids misuses per 10,000 persons (II)

(a) Hydrocodone



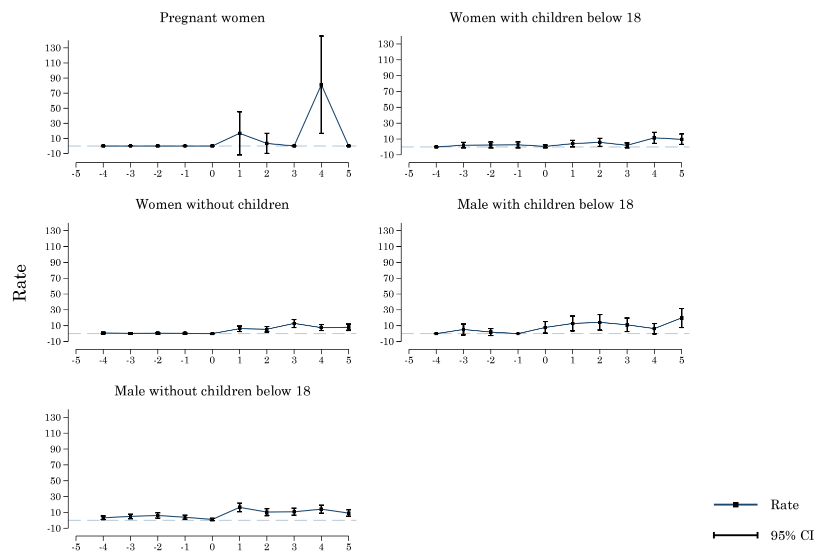
(b) Hydromorphone



Source: NSDUH

Figure 9: Synthetic opioids misuses per 10,000 persons

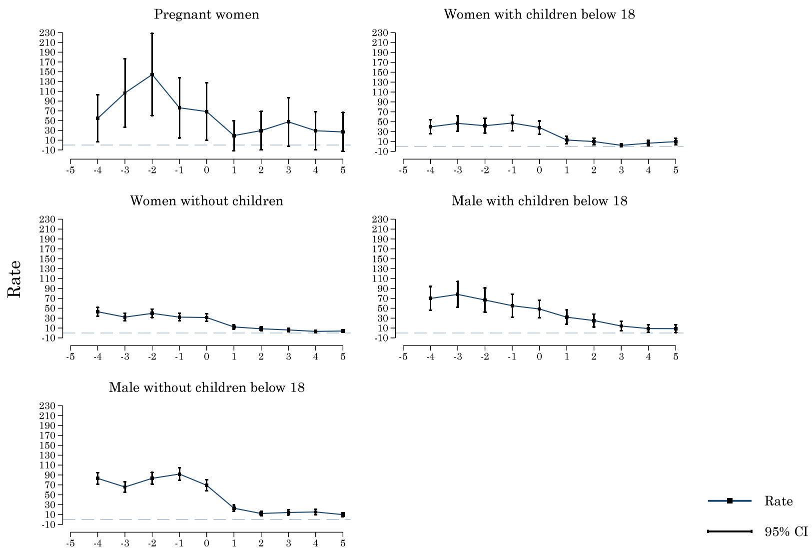
(a) Fentanyl



Source: NSDUH

Figure 10: Opioid agonists misuses per 10,000 persons in whole sample

(a) Methadone



(b) Buprenorphine

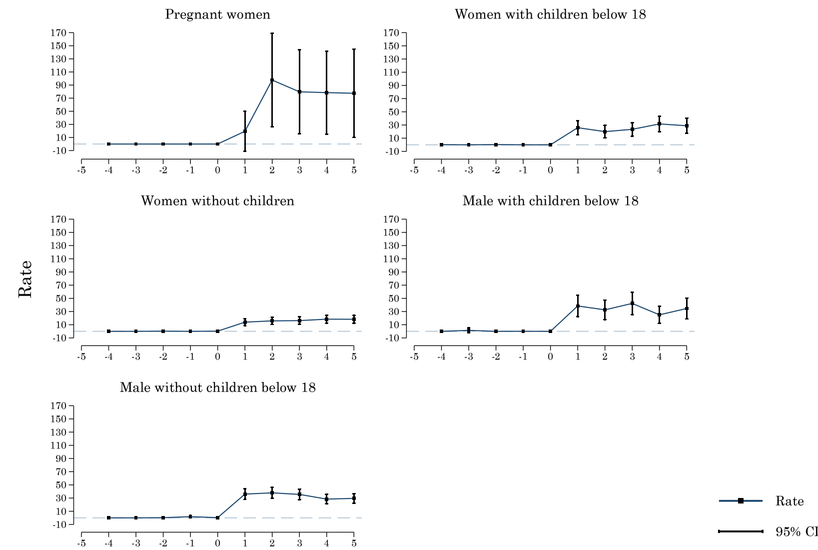
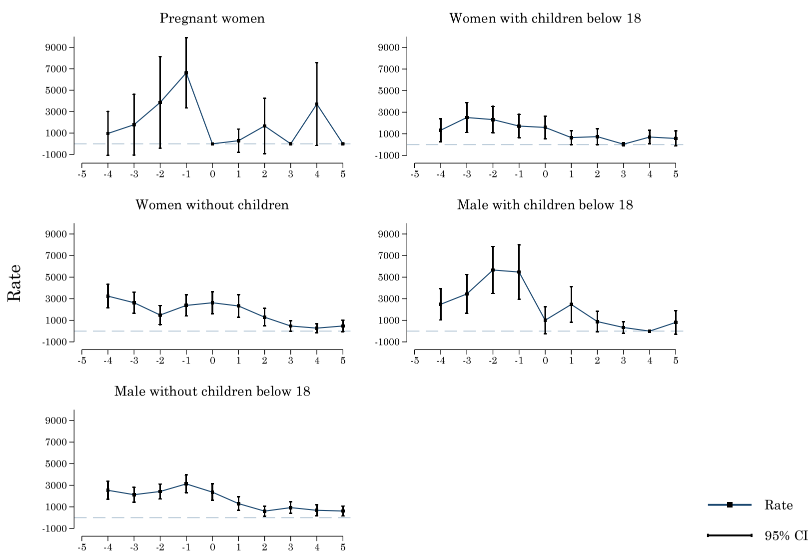
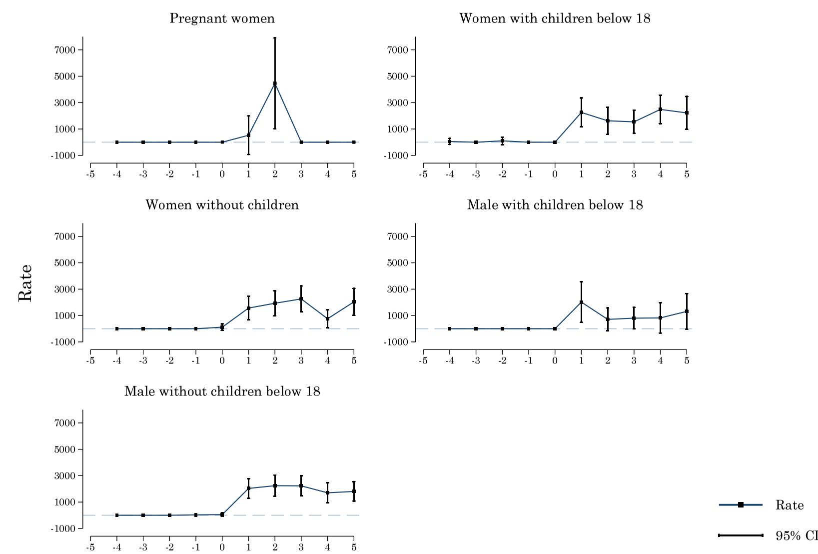


Figure 11: Opioid agonists misuses per 10,000 persons among patients receiving treatment for heroin and/or pain reliever dependence



(a) Methadone

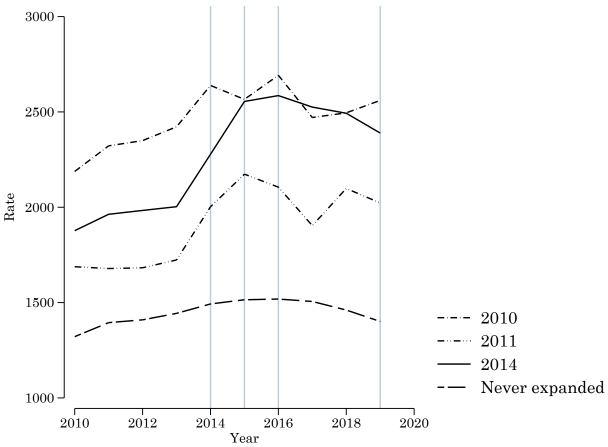


(b) Buprenorphine

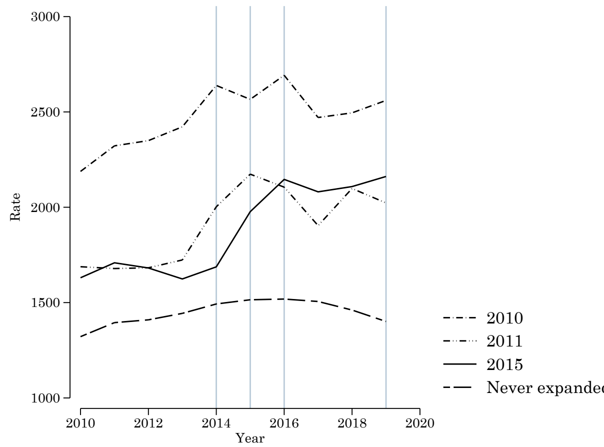
Source: NSDUH

Figure 14: Medicaid coverage rates for states grouped by expansion years

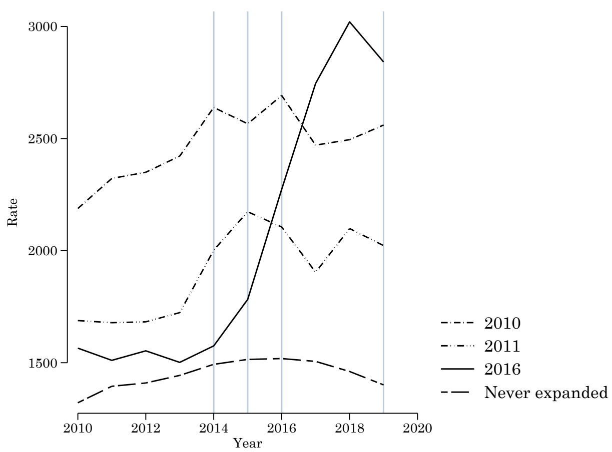
(a) 2010, 2011, 2014, non-expasion



(b) 2010, 2011, 2015, non-expasion



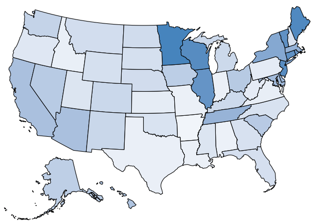
(c) 2010, 2011, 2016, non-expasion



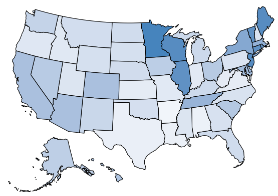
Data source: CPS

Figure 15: ACA income limits across states 2010-2019

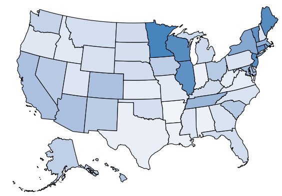
(a) 2010



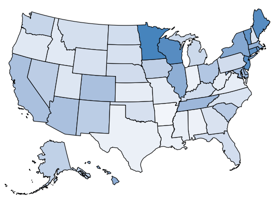
(b) 2011



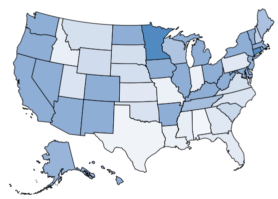
(c) 2012



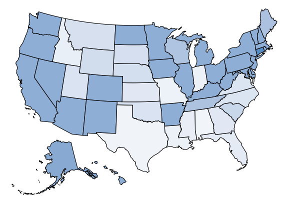
(d) 2013



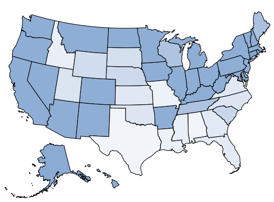
(e) 2014



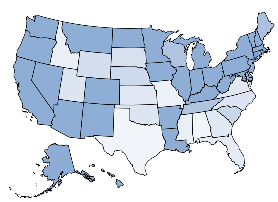
(f) 2015



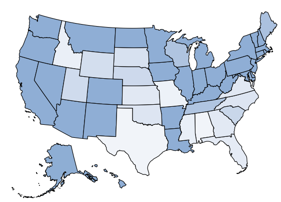
(g) 2016



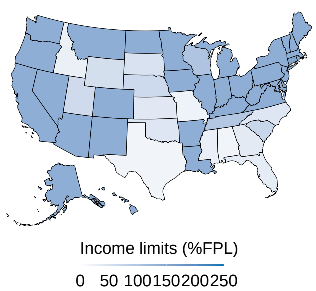
(h) 2017



(i) 2018



(j) 2019



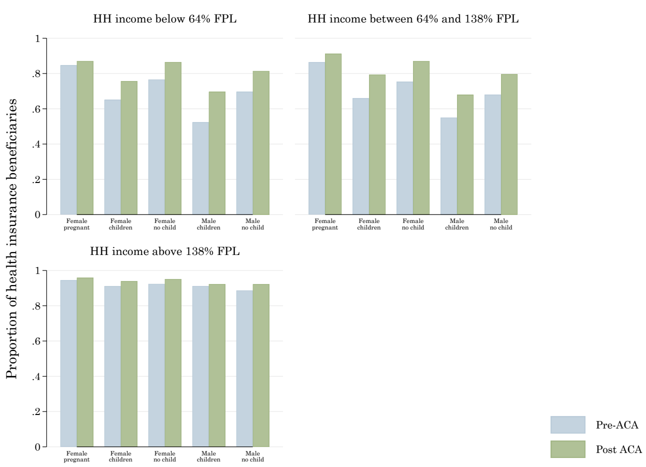
Source:Meinhofer and Witman (2018); KFF (2021)

Figure 16: Change in health insurance status before and after 2014

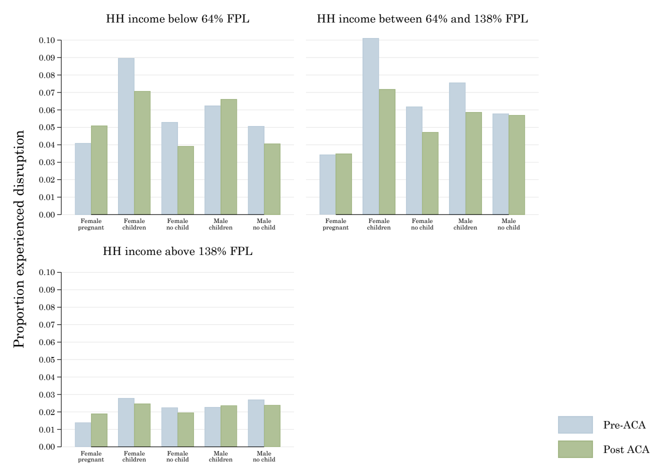
(a) Medicaid

(b) Private health insurance

(c) Any health insurane



(d) Health insurane loss in past 12 months



Data source: NSDUH

Table 3: Change in health insurance rate before and after 2014

	Pre-ACA	Post-ACA	Difference
		(a) Medicaid	
Pregnant women	0.3665	0.3775	0.0110
	(0.0134)	(0.0111)	(0.0174)
Mothers	0.1744	0.2272	0.0528***
	(0.0032)	(0.0027)	(0.0042)
Women without children	0.1228	0.1668	0.0440***
	(0.0020)	(0.0018)	(0.0027)
Fathers	0.0753	0.1115	0.0362***
	(0.0028)	(0.0026)	(0.0039)
Men without children	0.1068	0.1544	0.0475***
	(0.0017)	(0.0017)	(0.0024)
		(b) Overall health insurance	
Pregnant women	0.9075	0.9354	0.0279***
	(0.0079)	(0.0054)	(0.0096)
Mothers	0.8191	0.8874	0.0683***
	(0.0035)	(0.0022)	(0.0041)
Women without children	0.8781	0.9312	0.0531***
	(0.0021)	(0.0012)	(0.0024)
Fathers	0.8184	0.8750	0.0566***
	(0.0044)	(0.0028)	(0.0052)
Men without children	0.8353	0.8964	0.0611***
	(0.0023)	(0.0014)	(0.0027)
		(c) Private health insurance	
Pregnant women	0.5090	0.5536	0.0446*
	(0.0146)	(0.0115)	(0.0185)
Mothers	0.6127	0.6314	0.0187***
	(0.0044)	(0.0033)	(0.0055)
Women without children	0.6620	0.6648	0.0028
	(0.0033)	(0.0025)	(0.0041)
Fathers	0.7094	0.7258	0.0165**
	(0.0051)	(0.0038)	(0.0064)
Men without children	0.6289	0.6404	0.0115**
	(0.0032)	(0.0025)	(0.0041)
		(d) Insurance disruption	
Pregnant women	0.0239***	0.0274***	0.0035
	(0.0042)	(0.0037)	(0.0056)
Mothers	0.0523***	0.0396***	–0.0127***
	(0.0019)	(0.0013)	(0.0023)
Women without children	0.0307***	0.0240***	–0.0067***
	(0.0011)	(0.0007)	(0.0013)
Fathers	0.0351***	0.0313***	–0.0038
	(0.0021)	(0.0015)	(0.0026)
Men without children	0.0328***	0.0283***	–0.0045***
	(0.0010)	(0.0007)	(0.0012)
Observations	226,138	338,039	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses. Data sources: NSDUH (annually, 2010–2019), CPS (annually, 2011-2020). This table shows the changes in percentage of (a) Medicaid beneficiaries, (b) overall health insurance beneficiaries, (c) private health insurance beneficiaries, and (d) losing health insurance within the past 12 months for each gender-parent group. All means are weighted using analytic weights NSDUH provides.

Table 4: Summary table of changes in coverage rate among beneficiaries receiving treatments for substance use before and after 2014

	Pre-ACA	Post-ACA	Difference
	(a) Private insurance covering treatment for SUD patients		
Pregnant women	0.7577	0.8045	0.0468
	(0.0476)	(0.0323)	(0.0576)
Mothers	0.8639	0.8427	–0.0212
	(0.0088)	(0.0069)	(0.0112)
Women without children	0.8078	0.8187	0.0109
	(0.0088)	(0.0060)	(0.0106)
Fathers	0.8706	0.8372	–0.0334
	(0.0142)	(0.0132)	(0.0194)
Men without children	0.7991	0.7789	–0.0202
	(0.0120)	(0.0089)	(0.0149)
	(b) Medicaid covering treatment for SUD patients		
Pregnant women	0.2421	0.7756	0.5335***
	(0.0348)	(0.0355)	(0.0497)
Mothers	0.3318	0.7881	0.4563***
	(0.0191)	(0.0114)	(0.0222)
Women without children	0.3752	0.7516	0.3765***
	(0.0209)	(0.0124)	(0.0243)
Fathers	0.2309	0.7456	0.5147***
	(0.0328)	(0.0291)	(0.0439)
Men without children	0.3543	0.7716	0.4173***
	(0.0240)	(0.0138)	(0.0277)
Observations	226,138	338,039	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses. Data sources: NSDUH (annually, 2010–2019), CPS (annually, 2011-2020). This table shows the changes in percentage of SUD patients being covered by health insurance when they received treatment. Panel(a) shows the percentage of SUD treatment recipients with private health insurance being covered by health insurance for their treatment before and after 2014. Panel(b) shows the percentage of SUD treatment recipients with Medicaid being covered by Medicaid for their treatment before and after 2014. All means are weighted using analytic weights NSDUH provides.

Table 5: Summary of demographic and comorbidities across income groups of parenting women

Characteristics	Below 64% FPL	64–138% FPL	Above 138% FPL
Non-Hispanic white	0.3567	0.3755	0.6457
	(0.4790)	(0.4843)	(0.4783)
Non-Hispanic Black/African American	0.2193	0.2092	0.0973
	(0.4138)	(0.4068)	(0.2963)
Non-Hispanic Native American	0.0137	0.0093	0.0039
	(0.1161)	(0.0958)	(0.0623)
Non-Hispanic Hawaiian/other Pacific Islanders	0.0056	0.0076	0.0040
	(0.0746)	(0.0870)	(0.0629)
Non-Hispanic Asian	0.0297	0.0341	0.0841
	(0.1697)	(0.1814)	(0.2775)
Non-Hispanic multiracial	0.0186	0.0200	0.0134
	(0.1352)	(0.1400)	(0.1148)
Hispanic	0.3565	0.3443	0.1517
	(0.4790)	(0.4751)	(0.3588)
Graduated from highschool	0.6774	0.7809	0.9558
	(0.4675)	(0.4137)	(0.2056)
Unemployed	0.1117	0.0651	0.0220
	(0.3150)	(0.2467)	(0.1468)
Resides in metropolitan area	0.8233	0.8355	0.8815
	(0.3815)	(0.3708)	(0.3232)
Is married	0.4156	0.4020	0.7552
	(0.4928)	(0.4903)	(0.4300)
Has misused opioid before	0.0056	0.0052	0.0038
	(0.0748)	(0.0716)	(0.0612)
At high risk of heavy smoking	0.6819	0.7066	0.7559
	(0.4658)	(0.4554)	(0.4296)
Underwent distress past year	0.1888	0.1681	0.1174
	(0.3914)	(0.3740)	(0.3219)
Had depression before	0.1612	0.1608	0.1634
	(0.3677)	(0.3673)	(0.3697)
Has alcohol/illicit drug use problem before	0.0336	0.0410	0.0768
	(0.1802)	(0.1984)	(0.2663)
Median age	30–34	35–49	35–49
Observations	17198	16026	46868

Note: Standard deviation in parentheses. This table presents the weighted means and standard deviations of characteristics pertaining to demographics, human capital resources, and comorbidities. All means are weighted by analytic weight variable from NSDUH.

Table 6: Summary of pre-post 2014 changes in demographic and comorbidities across income groups of parenting women

Characteristics	Below 64% FPL	64–138% FPL	Above 138% FPL
Non-Hispanic white	0.0518***	0.0587***	0.0291***
	(0.0075)	(0.0080)	(0.0046)
Non-Hispanic Black/African American	-0.0078	-0.0044	0.0068**
	(0.0064)	(0.0065)	(0.0029)
Non-Hispanic Native American	0.0005	-0.0002	0.0003
	(0.0027)	(0.0024)	(0.0010)
Non-Hispanic Hawaiian/other Pacific Islanders	-0.0025*	-0.0010	-0.0003
	(0.0013)	(0.0014)	(0.0006)
Non-Hispanic Asian	-0.0029	-0.0024	-0.0124***
	(0.0021)	(0.0022)	(0.0021)
Non-Hispanic multiracial	0.0018	-0.0122***	-0.0025
	(0.0027)	(0.0027)	(0.0016)
Hispanic	-0.0408***	-0.0385***	-0.0210***
	(0.0071)	(0.0073)	(0.0034)
Graduated from highschool	-0.0246***	-0.0182***	-0.0117***
	(0.0072)	(0.0067)	(0.0022)
Unemployed	0.0253***	0.0105**	0.0081***
	(0.0053)	(0.0042)	(0.0016)
Resides in metropolitan area	-0.0162**	-0.0170**	-0.0137***
	(0.0066)	(0.0069)	(0.0039)
Is married	-0.0243***	-0.0066	-0.0108**
	(0.0073)	(0.0077)	(0.0045)
Has misused opioid before	0.0026*	0.0036**	0.0025***
	(0.0015)	(0.0014)	(0.0007)
At high risk of heavy smoking	0.0019	0.0070	0.0160***
	(0.0073)	(0.0075)	(0.0043)
Underwent distress past year	-0.0060	0.0099	-0.0028
	(0.0063)	(0.0064)	(0.0034)
Had depression before	0.0103*	0.0144**	0.0047
	(0.0060)	(0.0062)	(0.0038)
Has alcohol/illicit drug use problem before	0.0841***	0.1232***	0.3390***
	(0.0042)	(0.0051)	(0.0043)
Observations	17198	16026	46868

Note: Robust standard error in parentheses. This table presents the change in racial and socioeconomic composition, as well as proportion of comorbidities between before 2014 and after 2014 for each income group of parenting women.

Table 7: Difference-in-difference linear probability regression on Medicaid coverage rate using income cohorts as treatment. Sample: NSDUH

	(1)	(2)
Below 64% FPL	0.41***	0.3355 ***
	(0.0173)	(0.0175)
Post ACA	0.0500***	0.0495***
	(0.00398)	(0.00373)
Below 64% FPL × Post ACA	0.054	0.055 ***
	(0.0222)	(0.0218)
64–138% FPL	0.271***	0.198***
	(0.0130)	(0.0131)
64–138% FPL × Post ACA	0.1199 ***	0.1199***
	(0.0172)	(0.0171)
Non-Hispanic white		-0.0356***
		(0.00472)
Graduated from highschool		-0.104***
		(0.00896)
Unemployed		0.149***
		(0.0133)
Resides in metropolitan area		-0.0419***
		(0.00596)
Is married		-0.236***
		(0.00535)
Constant	0.126***	0.435***
	(0.00298)	(0.0106)
State fixed effects	No	No
Income fixed effects	Yes	Yes
Age fixed effects	No	Yes
Mean of Outcome	0.219	0.219
R^2	0.2254	0.274
BIC	77726.3	68752.3
N	80092	80092

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table reports the difference in changes to Medicaid coverage trends before and after 2014. Sample is defined as mothers aged 18–64 in years 2010–2019. Data source: NSDUH.

Table 8: Difference-in-difference linear probability regression on insurance loss rate using income cohorts as treatment. Sample: NSDUH

	(1)	(2)
Below 64% FPL	0.0620***	0.0486***
	(0.00574)	(0.00617)
Post	-0.00313	-0.00301
	(0.00213)	(0.00212)
Below 64% FPL × Post	-0.0159**	-0.0152**
	(0.00712)	(0.00714)
64–138% FPL	0.0734***	0.0633***
	(0.00652)	(0.00674)
64–138% FPL × Post	-0.0257***	-0.0257***
	(0.00777)	(0.00778)
Non-Hispanic white		-0.00379
		(0.00245)
Graduated from highschool		-0.00653
		(0.00481)
Unemployed		0.0461***
		(0.00898)
Resides in metropolitan area		-0.0132***
		(0.00342)
Is married		-0.0149***
		(0.00277)
Constant	0.0280***	0.0584***
	(0.00171)	(0.00615)
State fixed effects	No	No
Income fixed effects	Yes	Yes
Age fixed effects	No	Yes
Mean of Outcome	0.0414	0.0414
R^2	0.0145	0.0187
BIC	-32173.0	-32462.6
N	80092	80092

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table reports the difference in changes to rate of mothers losing insurance within past year before and after 2014. Sample is defined as mothers aged 18–64 in years 2010–2019. Data source: NSDUH.

Table 9: Difference-in-difference linear probability regression on Medicaid enrollment rate using income cohorts as treatment. Sample: CPS

	(1)	(2)
Below 64% FPL	0.385***	0.290***
	(0.00586)	(0.00631)
Post	0.0348***	0.0347***
	(0.00157)	(0.00159)
Below 64% FPL× Post No	0.0419***	0.0391***
	(0.00761)	(0.00772)
64–138% FPL	0.240***	0.184***
	(0.00493)	(0.00514)
64–138% FPL × Post	0.0813***	0.0815***
	(0.00651)	(0.00659)
Non-Hispanic white		-0.0217***
		(0.00194)
Graduated from high school		-0.0446***
		(0.00401)
Is unemployed		0.0766***
		(0.00239)
metropolitan		-0.0269***
		(0.00258)
Is married		-0.0886***
		(0.00250)
Constant	0.0585***	0.195***
	(0.00116)	(0.00514)
State fixed effects	No	No
Income fixed effects	Yes	Yes
Age fixed effects	No	Yes
Mean of Outcome	0.170	0.170
R^2	0.173	0.189
BIC	170047.5	156451.7
N	245759	232011

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table reports the difference in changes to Medicaid coverage trends before and after 2014. Sample is defined as mothers aged 18–64 in years 2010–2019. Data source: IPUMS CPS database.

Table 10: Difference-in-difference-in difference linear probability regression on Medicaid enrollment rate using income cohorts as treatment. Sample: CPS

	(1)	(2)
Expands in 2014	0.0341***	0.0351***
	(0.00231)	(0.00233)
Below 64% FPL	0.334***	0.236***
	(0.00807)	(0.00844)
Expands in 2014 × Below 64% FPL	0.104***	0.110***
	(0.0116)	(0.0117)
Post	0.0228***	0.0230***
	(0.00189)	(0.00192)
Expands in 2014 × Post	0.0240***	0.0237***
	(0.00312)	(0.00314)
Below 64% FPL × Post	0.0426***	0.0416***
	(0.0105)	(0.0107)
Expands in 2014 × Below 64% FPL × Post	0.00248	-0.00142
	(0.0150)	(0.0152)
64–138% FPL	0.184***	0.124***
	(0.00635)	(0.00654)
Expands in 2014 × 64–138% FPL	0.109***	0.115***
	(0.00967)	(0.00974)
64–138% FPL × Post	0.0589***	0.0592***
	(0.00845)	(0.00857)
Expands in 2014 × 64–138% FPL × Post	0.0514***	0.0508***
	(0.0127)	(0.0129)
Non-Hispanic white		-0.0196***
		(0.00192)
Graduated from high school		-0.0410***
		(0.00392)
Is unemployed		0.0754***
		(0.00236)
Resides in metropolitan area		-0.0385***
		(0.00257)
Is married		-0.0914***
		(0.00247)
Constant	0.0413***	0.185***
	(0.00140)	(0.00510)
State fixed effects	No	No
Income fixed effects	Yes	Yes
Age fixed effects	No	Yes
Mean of Outcome	0.170	0.170
R^2	0.191	0.207
BIC	164880.9	151250.1
N	245759	232011

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table reports the difference in changes to Medicaid coverage trends before and after 2014 among mothers with incomes below 64% FPL or 64–138% FPL in states expanding Medicaid in 2014. Sample is defined as mothers aged 18–64 in years 2010–2019. Data source: NSDUH.

Table 11: Difference-in-difference-in difference linear probability regression on Medicaid enrollment rate using income cohorts as treatment, excluding states adopting ACA before 2014. Sample: CPS

	(1)	(2)
Post	0.0362***	0.0382***
	(0.00235)	(0.00238)
Below 64% FPL	0.327***	0.230***
	(0.00832)	(0.00870)
Post × Below 64% FPL	0.112***	0.116***
	(0.0118)	(0.0118)
Post	0.0216***	0.0224***
	(0.00195)	(0.00199)
Post × Post	0.0252***	0.0243***
	(0.00316)	(0.00318)
Below 64% FPL × Post	0.0469***	0.0449***
	(0.0108)	(0.0110)
Post × Below 64% FPL × Post	-0.00184	-0.00472
	(0.0152)	(0.0154)
64–138% FPL	0.174***	0.116***
	(0.00654)	(0.00673)
Post × 64–138% FPL	0.119***	0.124***
	(0.00980)	(0.00987)
64–138% FPL × Post	0.0602***	0.0613***
	(0.00865)	(0.00878)
Post × 64–138% FPL × Post	0.0501***	0.0487***
	(0.0129)	(0.0130)
Non-Hispanic white		-0.0191***
		(0.00195)
Graduated from high school		-0.0402***
		(0.00397)
Is unemployed		0.0760***
		(0.00240)
Resides in metropolitan area		-0.0399***
		(0.00262)
Is married		-0.0901***
		(0.00251)
Constant	0.0392***	0.181***
	(0.00147)	(0.00518)
State fixed effects	No	No
Income fixed effects	Yes	Yes
Age fixed effects	No	Yes
Mean of Outcome	0.170	0.170
R^2	0.192	0.208
BIC	156516.9	143580.1
N	234569	221304

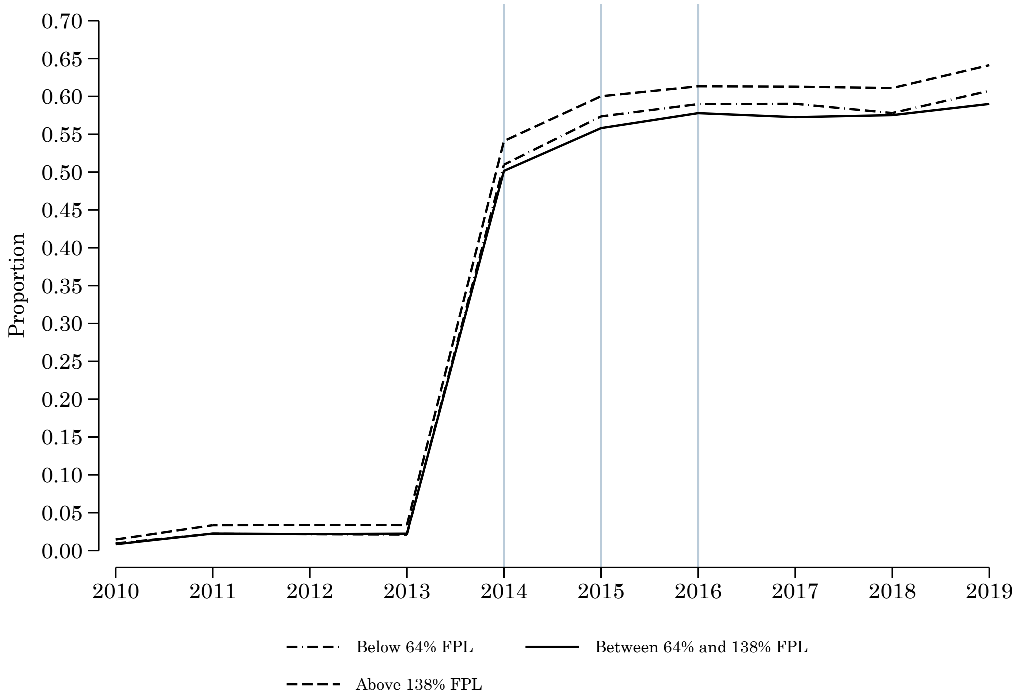
Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table reports the association between ACA adoption and Medicaid coverage rate for mothers with incomes below 64% FPL or 64–138% FPL. Data source: CPS, KFF, Meinhofer and Witman (2018)

Table 12: Three-way fixed effects Medicaid coverage rate using income cohorts as treatment. Sample: CPS

	(1)	(2)
2011	0.00877***	0.00742**
	(0.00316)	(0.00318)
2012	0.00582*	0.00555*
	(0.00311)	(0.00314)
2013	0.0335***	0.0341***
	(0.00351)	(0.00354)
2014	0.0360***	0.0358***
	(0.00333)	(0.00336)
2015	0.0443***	0.0437***
	(0.00344)	(0.00347)
2016	0.0537***	0.0537***
	(0.00347)	(0.00350)
2017	0.0484***	0.0471***
	(0.00354)	(0.00356)
2018	0.0489***	0.0484***
	(0.00340)	(0.00344)
2019	0.0540***	0.0541***
	(0.00361)	(0.00363)
Below 64% FPL in expanded states	0.108***	0.104***
	(0.00765)	(0.00777)
64–138% FPL in expanded states	0.177***	0.177***
	(0.00668)	(0.00678)
Non-Hispanic white		-0.0293***
		(0.00202)
Graduated from high school		-0.0458***
		(0.00390)
Is unemployed		0.0770***
		(0.00234)
Resides in metropolitan area		-0.0406***
		(0.00280)
Is married		-0.0884***
		(0.00245)
Constant	-0.00695	0.141***
	(0.00707)	(0.00839)
State fixed effects	Yes	Yes
Income fixed effects	Yes	Yes
Age fixed effects	No	Yes
Mean of Outcome	0.170	0.171
R^2	0.203	0.220
BIC	161719.2	148094.0
N	245759	232011

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table reports the association between ACA adoption and Medicaid coverage rate for mothers with incomes below 64% FPL or 64–138% FPL. Data source: CPS, KFF, Meinhofer and Witman (2018)

Figure 17: Proportions of mothers residing in a state that has expanded Medicaid by income groups



This figure shows the proportion of mothers residing in a state that has expanded Medicaid in a given year. Data source: CPS, KFF, Meinhofer and Witman (2018)

Table 13: Difference-in-difference regression on opioid misuse for parenting women

	(1)	(2)	(3)
Below 64% FPL	0.0294***	0.0157*	0.0324***
	(0.00744)	(0.00755)	(0.00764)
Post	-0.00233	-0.00103	0.0290***
	(0.00209)	(0.00207)	(0.00331)
Below 64% FPL × Post	-0.058	-0.004	-0.0294***
	(0.00948)	(0.00942)	(0.00943)
64–138% FPL	0.0223***	0.0115***	0.0256***
	(0.00485)	(0.00487)	(0.00502)
64–138% FPL × Post	-0.00157	-0.00189	-0.0195**
	(0.00687)	(0.00685)	(0.00678)
Non-Hispanic white	0.0225***	0.0258***	0.0167***
	(0.00219)	(0.00238)	(0.00227)
Graduated from highschool		-0.00189	-0.00534
		(0.00337)	(0.00330)
Unemployed		0.00954*	0.00467
		(0.00544)	(0.00533)
Resides in metropolitan area		0.00458	0.00559*
		(0.00301)	(0.00287)
married		-0.0264***	-0.0204***
		(0.00267)	(0.00256)
Has misused opioid before			0.722***
			(0.0345)
At high risk of heavy smoking			-0.00304
			(0.00242)
Underwent distress past year			0.0517***
			(0.00485)
Had depression before			0.0237***
			(0.00404)
Has alcohol/illicit drug use problem before			0.0654***
			(0.00665)
Received education about drugs/mental health			-0.0038
			(.00284)
Constant	0.0271***	0.0521***	0.0106
	(0.00199)	(0.0172)	(0.0168)
State fixed effects	No	No	
Income fixed effects	Yes	Yes	
Age fixed effects	No	Yes	
Mean of outcome	0.0383	0.0383	0.0383
R^2	0.00299	0.0106	0.0933
BIC	-37020.6	-37494.7	-44385.0
N	79588	79588	79588

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table reports the results for equation (4) on opioid misuse. Column (1) corresponds to results on pain reliever misuse trend, column (2) corresponds to results on prescription drug misuse trend, column (3) reports on substance use trends. Sample is defined as mothers aged 18–64 in years 2010–2019. Data source: NSDUH.

Table 14: Opioid misuse trends between income groups below 64% FPL and above 138% FPL

	(1)	(2)	(3)
Below 64% FPL × Post	-0.00561	-0.00509	-0.0278***
	(0.00949)	(0.00942)	(0.00944)
Demographics controls	No	Yes	Yes
Comorbidities controls	No	No	Yes
State fixed effects	No	No	No
Income fixed effects	Yes	Yes	Yes
Mean of outcome	0.0374	0.0374	0.0374
R^2	0.00256	0.0107	0.0914
BIC	-34796.7	-35243.6	-41227.1
N	70964	70964	70964

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table reports the difference in changes to opioid misuse trends before and after 2014. Sample is defined as mothers aged 18–64 in years 2010–2019 with income below 64% FPL or above 138% FPL. Data source: NSDUH.

Table 15: Opioid misuse trends between income groups 64–138 % FPL and above 138% FPL

	(1)	(2)	(3)
64–138% FPL× Post	-0.00199	-0.00214	-0.0161**
	(0.00687)	(0.00685)	(0.00679)
Demographics controls	No	Yes	Yes
Comorbidities controls	No	No	Yes
State fixed effects	No	No	No
Income fixed effects	Yes	Yes	Yes
Mean of outcome	0.0377	0.0377	0.0377
R^2	0.00263	0.0105	0.0946
BIC	-35602.6	-36054.7	-42556.5
N	73835	73835	73835

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table reports the difference in changes to opioid misuse trends before and after 2014. Sample is defined as mothers aged 18–64 in years 2010–2019 with income 64%–138% FPL or above 138% FPL. Data source: NSDUH.

Table 16: DD on other substance misuse outcome

	(1)	(2)	(3)
	Pain reliever	Prescription drugs	Substances
Below 64% FPL × Post	-0.0404***	-0.0461***	-0.0388**
	(0.00967)	(0.0103)	(0.0144)
64–138% FPL × Post	-0.0241**	-0.0280***	-0.0243***
	(0.00741)	(0.00850)	(0.0113)
Demographics controls	No	Yes	Yes
Comorbidities controls	No	No	Yes
State fixed effects	No	No	No
Income fixed effects	Yes	Yes	Yes
Mean of outcomes	0.042	0.0606	0.1547
R^2	0.105	0.0984	0.108
BIC	-38614.8	-10281.7	55480.0
N	80092	80092	80092

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table reports the results for replication of equation (4) on alternative outcomes. Column (1) corresponds to results on pain reliever misuse trend, column (2) corresponds to results on prescription drug misuse trend, column (3) reports on substance use trends. Sample is defined as mothers aged 18–64 in years 2010–2019. Data source: NSDUH.

Table 17: DD regression for opioid misuses with one pre-ACA period

	(1)	(2)	(3)
Below 64% FPL × Post	-0.0175***	-0.0173	-0.0606***
	(0.0154)	(0.0154)	(0.0154)
64–138% FPL × Post	0.00449	0.00453	-0.0304***
	(0.00739)	(0.00739)	(0.00783)
Demographics controls	No	Yes	Yes
Comorbidities controls	No	No	Yes
State fixed effects	No	No	No
Income fixed effects	Yes	Yes	Yes
Mean of outcomes	0.0378	0.0378	0.0378
R^2	0.00279	0.00305	0.0322
BIC	-27723.3	-27996.7	-33688.9
N	58457	58457	58457

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table reports the differences in opioid misuse change among mothers with only one year pre-treatment. Sample is defined as mothers aged 18–64 in years 2013–2018 (2014–2019 in survey) Data source: NSDUH.

Table 18: DD regression for other substance use outcomes with one pre-ACA period

	(1)	(2)	(3)
	Pain relievers	Prescription drugs	Substances
Below 64% FPL × Post	-0.0688***	-0.0838***	-0.0775***
	(0.0159)	(0.0164)	(0.0208)
64–138% FPL × Post	-0.0312**	-0.0400**	-0.0490*
	(0.00800)	(0.00889)	(0.0124)
Demographics controls	No	Yes	Yes
Comorbidities controls	No	No	Yes
State fixed effects	No	No	No
Income fixed effects	Yes	Yes	Yes
Mean of outcomes	0.0412	0.0607	0.159
R^2	0.113	0.106	0.112
BIC	-29601.3	-4169.7	44206.4
N	58457	58457	58457

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table reports the differences in pain reliever, prescription drugs, and substance use problems change among mothers with only one pre-treatment year. Sample is defined as mothers aged 18–64 in years 2013–2019 Data source: NSDUH.

Table 19: Parallel trend assumption test between poor/near-poor and non-poor mothers' Medicaid coverage and insurance loss before ACA adoption wave in 2014

	(1) 2010–2012	(2) 2011-2013	(3) 2012–2014
	(a) Opioid misuse		
Below 64% FPL × Post	0.004	0.00533	0.0288***
	(0.0139)	(0.0200)	(0.0119)
64–138% FPL × Post	-0.000610	-0.0122	-0.0131
	(0.0158)	(0.0132)	(0.0121)
	(b) Prescription drug use problems		
Below 64% FPL × Post	0.00656	0.00266	0.0190
	(0.0156)	(0.0216)	(0.0236)
64–138% FPL × Post	0.000141	-0.0118	-0.0109
	(0.0191)	(0.0189)	(0.0174)
	(c) Substance use problems		
Below 64% FPL × Post	0.00690	-0.0165	0.0192
	(0.0167)	(0.0170)	(0.0170)
64–138% FPL × Post	-0.0133	0.000870	-0.00252
	(0.0176)	(0.0169)	(0.0170)
	(d) Medicaid coverage		
Below 64% FPL × Post	-0.0151	-0.00970	0.0389
	(0.0271)	(0.0275)	(0.0247)
64–138% FPL × Post	0.0506**	0.0249	0.0350
	(0.0256)	(0.0264)	(0.0245)
	(e) Insurance loss		
Below 64% FPL × Post	-0.0113	0.0152	0.00560
	(0.0144)	(0.0178)	(0.0130)
64–138% FPL × Post	-0.0274	0.0274	-0.0109
	(0.0172)	(0.0192)	(0.0143)
Demographics controls	Yes	Yes	Yes
Comorbidities controls	Yes	Yes	Yes
State fixed effects	No	No	No
Income fixed effects	Yes	Yes	Yes

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table reports the replicated results from equation (5) in the first row and equation (6) in the second row of each panel. Panel (a) reports pre-treatment rate of change differences for opioid misuse, panel (b) reports results for prescription drug uses, panel (c) reports results for substance uses, panel (d) reports results for Medicaid coverage, and panel (e) reports results for health insurace loss. Column 1 presents association between the false Post period with outcomes in 2010–2012, with 2011 and 2012 assigned "post" status. Column 2 association between the false Post period with outcomes in 2011–2013, with 2012 and 2013 assigned "post" status. Column 3 presents the difference in misuse changes in 2012–2014, with 2013 and 2014 assigned "post" status. Data source: NSDUH.

Figure 18: Comparison of DD effect sizes on Medicaid coverage and placebo distribution

(a) Below 64% FPL × Post and placebo distribution (b) 64–138% FPL × Post and placebo distribution

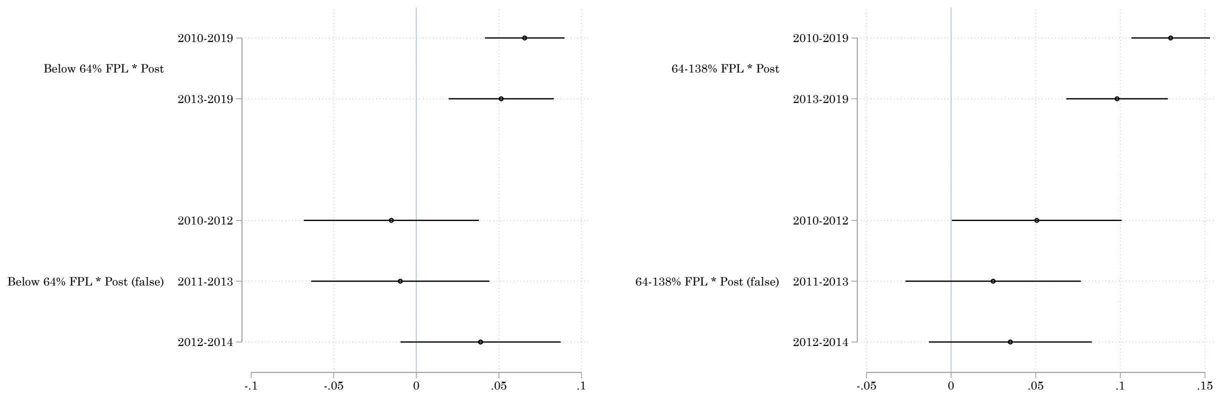
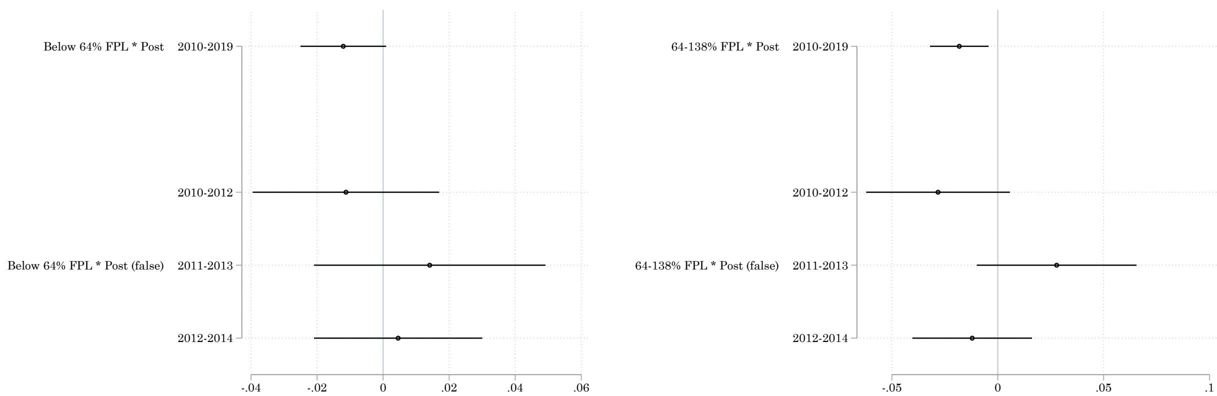
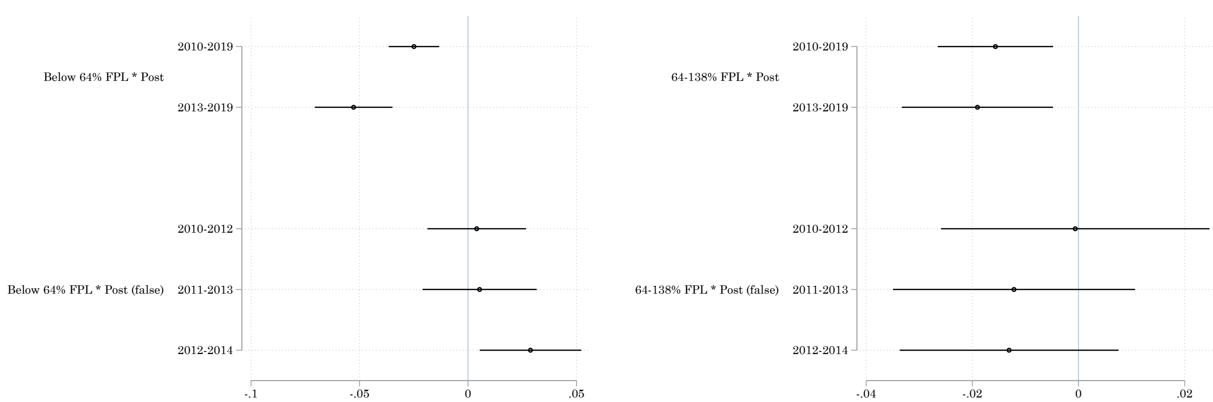


Figure 19: Comparison of DD effect sizes on insurance loss and placebo distribution



(a) Below 64% FPL × Post (b) 64%–138% FPL × Post

Figure 20: Comparison of DD effect sizes on opioid misuse and placebo distribution



(a) Below 64% FPL × Post and placebo distribution (b) 64–138% FPL × Post and placebo distribution

This figure plots the distribution of the coefficient associated with the interaction between a treatment group and the post status of a year. Panel (a) illustrates the coefficients of regressions in table 14 (row 2010–2019), 17 (row 2013–2019), and 19 (rows 2010–2012, 2011–2013, 2012–2014) for comparing between poor and non-poor mothers with 95% CI. Panel (b) illustrates the coefficients of regressions in table 15 (row 2010–2019), 17 (row 20132019), and 19 (rows 2010–2012, 2011–2013, 2012–2014) for comparing between near-poor and non-poor mothers with 95% CI.

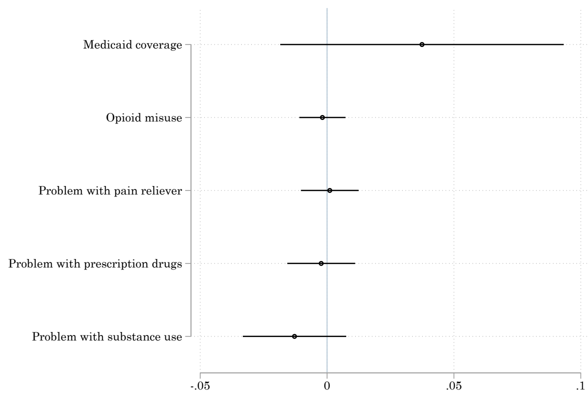
Table 20: Falsification test on women aged 65 and above with treatment group being 64–138% FPL and comparison group being above 138% FPL

	(1) Medicaid coverage	(2) Opioid misuse	(3) Pain reliever	(4) Prescription drugs	(5) Substances
Below 64% FPL × Post	0.0374	-0.00182	0.00107	-0.00230	-0.0128
	(0.0285)	(0.00465)	(0.00580)	(0.00682)	(0.0104)
64%–138% FPL × Post	0.0308	0.000379	-0.000231	-0.0111	-0.0294**
	(0.0247)	(0.00926)	(0.00931)	(0.00976)	(0.0128)
Demographics controls	Yes	Yes	Yes	Yes	Yes
Comorbidities controls	No	Yes	Yes	Yes	Yes
State fixed effects	No	No	No	No	No
Income fixed effects	Yes	Yes	Yes	Yes	Yes
Mean of outcome	0.100	0.00941	0.0102	0.0178	0.0408
R^2	0.214	0.140	0.129	0.0762	0.0520
bic	3558.9	-34856.8	-33164.6	-22535.6	-7886.5
N	17612	17612	17612	17612	17612

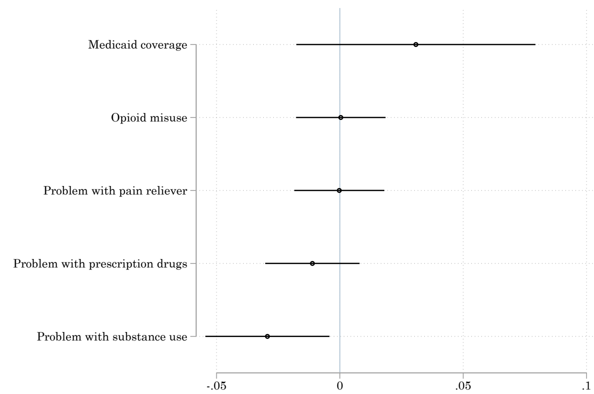
Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table reports the replicated results of regression (4) on women aged above 65. Column (1) reports the results with the same demographics controls as in column (2) of table 7. Column (2)–(5) report the results with the same controls for demographics, comorbidities, and drugs education as column (3) in table 13 on opioid misuse, problem with pain reliever use, problem with prescription drug use, and problem with substance use, respectively. Sample is defined as women aged above 65. Data source: NSDUH.

Figure 22: ACA impacts on change in Medicaid coverage growth and trends of substance use problems among women aged 65 and above

(a) Below 64% FPL × Post



(b) 64%–138% FPL × Post



This figure plots the distribution of the coefficient associated with the interaction between a treatment income group and the post-treatment status of a year among women aged 65 and above as reported in table 20 . Panel (a) illustrates the coefficients of regressions in for comparing between below-64% and above-64% FPL mothers with 95% CI. Panel (b) illustrates the coefficients for comparing between 64–138% FPL and below-64% FPL/above 138% FPL combined with 95% CI.