Born Addicted: Mandatory Prescription Drug Monitoring Programs, Opioids, and Neonatal Abstinence Syndrome

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Abstract

A growing body of research has shown the significant effects of mandatory Prescription Drug Monitoring Programs (PDMPs) on various outcomes related to the opioid epidemic in the United States. This study aims to identify first, the effects of mandatory PDMPs on opioid prescription rates, and second, the effects of these policies on hospital use measures and rates of Neonatal Abstinence Syndrome. Utilizing the Synthetic Control Method, I find that mandatory provisions significantly reduce state-level opioid prescription rates. While I find no significant results pertaining to hospital use, I find that these policies are associated with significant increases in cases of Neonatal Abstinence Syndrome, particularly among the Medicaid population.

Introduction

The misuse and addiction of opioids, particularly prescription pain relievers, heroin, and synthetic opioids, is a national health crisis with severe detrimental effects on public health and the economy. In 2017, the Council of Economic Advisors estimated that the economic cost of prescription drug abuse arising from lives-lost, medical treatment, crime, and decreased productivity totals around $500 billion per year.

The first wave of increased opioid prescribing began in the 1990s, followed by subsequent rapid increases after 2010 (CDC 2011). These dramatic increases in prescribing behavior were partly due to changes in the healthcare system. In 2005, when Medicare changed its reimbursement system for hospitals, it linked inpatient payments to the Hospital Consumer Assessment of Healthcare Providers and Systems, which included performance of pain management as one of its seven primary measures. Later, when the

Affordable Care Act passed, pain management scores were used as core components in patient experience performance measures, which were used to determine value-based incentive payments given to hospitals (Powell 2015). By 2014, the National Survey on Drug Use and Health reported that prescription drug abuse was second in prevalence only to marijuana, while other studies have shown that four out of five new heroin users initiated drug use with prescription opioids (Jones et al. 2013).

Drug overdose deaths involving any opioid (prescription opioids, synthetic opioids, and heroin) rose from 18,515 to 47,600 deaths per year from 2007-2017 (National Institute on Drug Abuse). Notably, more than 68% of the opioid-related deaths after 2010 were attributed to males and young adults (Ruhm 2019). However, women, particularly of maternal age, have also constituted a growing share of the opioid affected population. Approximately 28% of privately-insured and 39% of Medicaid enrolled women ages 15–44, filled a prescription for an opioid medication each year from 2008–2012. Maternal opiate use in pregnancy increased from 1.19 per 1,000 births in 2000 to 5.63 in 2009, with 60% of these mothers covered by Medicaid (Stover 2015).

Simultaneously, the incidence of babies born with drug withdrawal symptoms, also known as Neonatal abstinence syndrome (NAS), has sharply risen. The CDC reports that in 2014, an estimated 32,000 newborns were born with NAS, equivalent to one opioid withdrawal birth every 15 minutes- a more than five-fold increase from 2004. Among mothers on Medicaid, NAS incidence also increased more than five-fold during this time period, with 14.4 per 1,000 births in 2014. These infants were significantly more likely to be transferred to other hospitals and have longer lengths of stay than those born without NAS, or those born with NAS whose mothers were covered under private insurance. An estimated $462 million were attributed to total hospital costs for NAS babies covered by Medicaid in 2014, up from $65.4 million in 2004 (Winkelman 2018).

Not only does the growing prevalence of NAS pose significant costs for hospitals and patients, but also, newborns born with NAS are more likely than others to suffer from low birthweight, respiratory complications, and sudden infant death syndrome (SIDS). Evidence also shows that opioid-exposed newborns have impaired neurocognitive and physical development from age 6 months through adolescence (Yeoh et al. 2019). Since

the growth of maternal opioid use is higher than the incidence of NAS, it is evident that not all babies exposed to opioids in the womb exhibit symptoms (Stover 2015).

In an effort to combat prescription drug abuse and diversion, many states have implemented initiatives known as Prescription Drug Monitoring Programs (PDMPs). These programs collect, monitor, and analyze data on patient drug prescriptions, submitted by drug prescribers and dispensers, in order to identify patients who may be doctor-shopping or abusing prescription drugs. Currently, 49 states have PDMPs, but specific protocol greatly varies by state. Many of these state programs do not mandate prescriber or dispenser-use of the electronic system, while more recent policies mandate access only under particular circumstances. For example, New Jersey requires dispensers to query the system prior to dispensing drugs for every patient every time, while Ohio mandates that prescribers use the system when prescribing to chronic pain patients only. While these mandatory regulations have received pushback from doctors, who cite costliness of querying the system, authorities such as the CDC maintain that PDMPs are only effective insofar as doctors are forced to utilize the data.

I contribute to the current literature relating to the effects of these policies by first, estimating the effects of mandatory PDMPs on state-level opioid prescription rates. Second, given changes in opioid prescription rates, I estimate the effects of mandatory PDMPs on opioid-related hospital inpatient and emergency department admittance rates, and on the incidence of Neonatal Abstinence Syndrome, using the synthetic control method. I find that mandatory PDMPs significantly reduce state-level opioid prescription rates by 13 prescriptions per 100 persons on average, and these decreases grow over time. Additionally, while I find no significant effects on hospital opioid-incident data, I find significant increases in the incidence of NAS of 5 per 1,000 newborn hospitalizations on average, and in particular, an increase of 12 per 1,000 newborn hospitalizations for mothers on Medicaid.

1 Background

A small, but growing body of literature has shown inconsistent effects of PDMPs on drug-related outcomes. Studies that focus on non-mandatory programs, uncover little to no effects on measures related to prescription drug abuse (Brady et al. 2014). By contrast, recent studies which estimate the effects of mandatory programs demonstrate significant differences in outcomes related to drug abuse including; decreases in drug-abuse treatment center admissions (Grecu et al. 2019), violent crime rates (Dave et al. 2018), and foster-care admissions due to child neglect (Gihleb et al. 2018). Other authors report that while mandatory PDMPs decrease the supply of certain prescription opioids, evidence is suggestive of substitution towards more dangerous drugs (Mallatt 2017, Meinhofer 2018).

Bachmueller and Cary (2018) find that mandatory PDMPs are associated with significant decreases in measures of excessive quantity and doctor-shopping behavior, but find no changes in opioid poisonings. However, their study is limited to the Medicare population and does not represent a large fraction of the opioid-abusing population, including young adults and those with higher incomes. Grecu et. al (2019) find that young adults ages 18-24 are particularly affected by the implementation of mandatory PDMPs, and uncover significant decreases in substance abuse treatment center admissions for this age group. However, focusing solely on treatment center admissions as a measure of abuse limits this result to those that are more likely to be admitted to treatment centers due to income or family background, and fails to encompass the entire population who may be abusing drugs or susceptible to opioid poisonings.

While Meinhofer (2018), focuses specifically on drug poisonings, and finds some evidence of decreases in this measure post-implementation of a mandatory PDMP, she also finds some weak evidence of substitution towards more dangerous drugs, including heroin and cocaine.

However, there are no existing studies which focus on the effects of these policies specifically for women of maternal age, or on NAS births. Research has shown that between the years 2009-2011, 28% of pregnant women filled at least one opioid prescription during pregnancy. These women were more likely to be white and have depression. Additionally,

it has been shown that higher cumulative exposure to short-acting preparations, cigarettes, and SSRIs were associated with greater risk of developing NAS (Patrick et al 2015). It remains unclear as to whether exposure to opioids in higher doses increases the severity of NAS, resulting in potentially longer and more costly hospital stays.

To the extent that pregnant women who are overprescribed opioids during pregnancy constitute a significant portion of mothers who give birth to babies with NAS, I expect to observe decreases in instances of NAS. However, it is also possibile that opioid users substitute towards other substances like cigarettes or SSRIs when prescription opioids are more difficult to obtain, increasing the prevalence of NAS. While opioid users may also substitute towards more dangerous, illegal drugs such as heroin or cocaine, babies exposed to these drugs may be likely to be classified under different diagnosis codes, including those reserved for babies exposed to cocaine, hallucinogenics, or other narcotics, and would not be included under the NAS criterion that I use. Further, the extent to which previous authors observe substantial decreases in proxies of abuse for young adult males, may point to a difference in prescribing behavior for certain groups. Doctors may simply be less suspect of young women as potential abusers than young men, and may be less responsive to mandatory PDMPs when it comes to women.

It should also be noted that many of the previous results in the PDMP literature should be questioned due to widespread discrepancies in policy implementation dates. Horwitz et al. (2018) find that many of the dates most commonly used in the current literature lead to drastically different results. I take a more rigorous approach to verifying mandatory implementation dates and conduct the first study that I am aware of on the effects of these policies on the incidence of NAS in the United States.

2 Data

2.1 Prescription Rate Data

Yearly county and state-level prescription rates from 2006-2017 were obtained from the Centers for Disease Control Injury Center. These data, which are collected from

IQVIA Xponent, are based on a sample of approximately 50,000 retail pharmacies, which dispense nearly 90% of all retail prescriptions in the US. A prescription is an initial or refill prescription dispensed at a retail pharmacy in the sample and paid for by commercial insurance, Medicaid, Medicare, cash or its equivalent. These data do not include mail-order pharmacy data, nor do they include drugs dispensed at hospitals. Prescription rates are total number of opioid prescriptions per 100 persons, where opioids include; buprenorphine, codeine, fentanyl, hydrocodone, hydromorphone, methadone, morphine, oxycodone, oxymorphone, proxoxyphene, tapentadol, and tramadol, and exclude cold and cough formulations containing opioid products. Unfortunately, these publicly available data do not include any information regarding the demographic breakdown of prescription rates, such as age, sex, or race. In order to better implement the Synthetic Control Method, I use prescription rates on the state level.

Due to the fact that no comparable data are available for time periods prior to 2006, during which several states enacted non-mandatory PDMPs, I focus on identifying the effects of having mandatory policies, rather than estimating differences in effects between non-mandatory and mandatory policies.

I initially gathered PDMP implementation dates through the Prescription Drug Abuse Policy System (PDAPS). These data are compiled by Legal Science, a third-party, and are cross-examined by content experts. Due to the great skepticism surrounding the validity of the implementation dates that are publicly available through PDAPS and others, I also gathered implementation dates from Justine Mallatt, who compiled an original dataset of implementation dates for her job market paper at Purdue University. I cross-referenced Justine's dates with the PDAPS dates, and in the case of any discrepancy, corrected implementation dates from original state legislative sources. In these cases, I coded the states as having implemented a mandatory PDMP if the policy required either dispensers or prescribers to query the system for at least some patients, and the policy had not only been passed, but already implemented. I acquired non-mandatory PDMP implementation dates from Horwitz et al. (2018). I do not subset these data by whether the mandatory policy requires access for every patient, new patients only, or chronic-pain patients, as there are limited states in each of these categories, constituting a small sample

size for evaluating the various effects of these mandatory sub-categories.

State-level local area unemployment rates from 2006-2017 are obtained through the Bureau of Labor Statistics, and age-adjusted state-level population data for the relevant years were obtained through SEER Cancer Research. Additionally, I control for alcoholic beverage tax rates, obtained through the State and Local Finance Initiative, for years 2006 - 2017. Kenkel (2005) shows that alochol tax rates are fully passed through to consumer alcohol prices and changes in tax rates are good proxies for prices of alcohol, a possible substitute for opioids. I also control for percent of the population who have health insurance, on the state level, obtained from the Henry J. Kaiser Family Foundation (2006-2017), and per capita personal income levels on the state level, which were obtained from the Bureau of Labor Statistics (2006-2017).

I control for other laws, which vary across states and time, and potentially impact opioid prescription rates. These include Physical Exam Requirement (PER) laws, which require that a licensed practitioner conduct a physical exam before prescribing opioids to a patient, ID laws, which require patients to present valid government-issued identification upon obtaining prescriptions, "Pill Mill" laws, which regulate pain management clinics, and recreational marijuana laws. Implementation dates for "Pill Mill" and recreational marijuana laws were obtained by PDAPS. Indicators for PER and ID laws, were coded by state in each year according to whether the state had implemented any such law. These dates were obtained from the Center for Disease Control, and any missing dates were cross-referenced with state legislature websites.

2.2 Opioid Hospital Use and NAS Data

Opioid-related hospital use data and Neonatal Abstinence Syndrome data are obtained from the Healthcare Cost Utilization Project (HCUP). The opioid-related hospital use data reports annual rates of either inpatient cases or emergency department visits per 100,000 population by demographic, on the state-year level. A hospital use is considered opioid-related in the presence of certain ICD diagnosis codes. Prior to October 1, 2015, under the ICD-9, these were opioid type dependence, combinations of opioid type drug with any other drug, opioid abuse, poisoning by opium or poisoning by opiate antagonists,

and accidental poisoning by heroin, methodone, or other opiates, heroin or other opiates causing adverse effects in therapeutic use. After October 1, 2015, in the wake of the change to ICD-10, these codes were; opioid-related disorders, poisoning by or adverse effect of; opium, heroin, other opioids, methadone, other synthetic narcotics, unspecific narcotics, other narcotics. The unit of analysis is a hospital discharge, meaning that if a patient is admitted to the ED on several occasions in a single year, these are each counted as separate discharges. Records for patients admitted to the ED and then transferred to an acute care hospital are counted as inpatient stays.

HCUP has specified that researchers should remain extremely cautious of opioid-related hospital use time trends before and after this diagnostic change, as there are systematic discontinuities in the data across states, and the rates recorded for 2015 were based upon only three out of four quarters of data.

The Neonatal Abstinence Syndrome data contain the number of NAS hospitalizations per 1,000 newborn hospitalizations on the state-year level from 2008-2018. The rate per 1,000 newborn hospitalizations are stratified by sex, expected payer, urbanicity, and income quartile. Prior to October 1, 2015, in ICD-9, a diagnosis of neonatal abstinence syndrome included drug withdrawal syndrome in a newborn (code 779.5), while after October 1, 2015 an NAS diagnosis referred to neonatal withdrawal symptoms from maternal drugs of addiction (code P96.1). Both prior to 2015 and after 2015, these diagnosis codes are distinct from those which specify withdrawal from other particular drugs including; alcohol, hallucinogenics, and cocaine. Thus, while the diagnosis codes that I analyze are more likely to include newborns affected by opioids (depending on how easily a diagnosis can be made at the time of birth), there is likely some overlap with other drug withdrawal categories. As with the hospital data, the change in the ICD codes resulted in a discontinuity in rates across 2015, and the 2015 rates are based only on three out of four quarters of data.

Additionally, I had hoped to obtain data on sales and prices of other viable substitutes for opioid abusers, such as street drugs like heroin and cocaine, cigarettes, and SSRIs, but I was unable to obtain sufficient data for the years that I needed.

3 Methodology

3.1 Difference in Difference

I exploit the variation in the timing of adoption of mandatory PDMPs through a standard difference-in-differences (DD) framework, to estimate effects of these policies on state-level opioid prescription rates.

First, I employ an event-study analysis, following Grecu et al. (2019), which estimates the following specification:

$$Y_{it} = \beta_0 + \beta_1 Non-Mand_{it} + \beta_2 Mand_{it=-3} + \beta_3 Mand_{it=-2} + \beta_4 Mand_{it=-1} + \beta_5 Mand_{it=1} + \beta_6 Mand_{it=2} + \beta_7 Mand_{it=3} + \beta_8 Controls_{it} + \beta_9 State_i + \beta_{10} Year_t + \beta_{11}(State_i * Year_t) + u_{it} \quad (1)$$

The dependent variable Y_{it} measures the prescription rate per 100 persons in state i in year t. The variable $Mandatory_{it}$ is an indicator denoting whether state i adopted a mandatory PDMP in time period t, where t= 0 is the year in which the policy was initially enacted. $Mandatory_{it}$ is divided into pre-treatment and post-treatment phases.

The coefficients β_2 through β_7, estimate the average change in prescription rate in state i in pre and post-adoption periods, as compared to the initial treatment period, $t = 0$.

This analysis allows me to assess the critical assumption necessary for the DD analysis, that states which have not yet enacted mandatory policies are valid counterfactuals for treated states, and to further estimate how the effects of these policies, once implemented, change over time. In all specifications, I control for a set of potential confounding variables which vary across states and time, and which may affect prescription rates. $Controls_{it}$ represents a set of state and time-varying variables including; unemployment rates, alcohol tax rates, and state-level population, in addition to other state-regulated laws that target opioid abuse. These include; Physical Exam Requirement laws, ID laws, recreational marijuana legalization, and "Pill Mill" laws.

$State_i$ are state fixed effects, which control for state-specific characteristics that may influence prescription rates, such as cultural attitudes towards drugs and other state-regulated laws. $Year_t$ are year fixed effects which control for effects that vary across

time and are common to all states, such as federal laws, changes in long-term economic conditions, and the change from ICD-9 to ICD-10 in 2015, in regressions where Y_{it} is Hospital use or NAS rate in state i in year t.

$(State_i * Year_t)$ are state-specific trends which control for differential linear trends in prescription rates across states, relative to control states that might affect the likelihood of policy adoption, and if otherwise uncontrolled for may bias the estimates of interest. Including state-specific trends also allows the strict assumption that states follow common prescription rate trends to be relaxed. Further, state-specific trends allow states to adopt to the change in ICD codes differently. Additionally, I control for variation in the timing of adoption of non-mandatory policies through the variable $Non-Mandatory_{it}$, which indicates if state i adopted a non-mandatory PDMP in year t.

I then estimate the following specification:

$$\begin{aligned} Y_{it} &= \beta_o + \beta_1 Non-Mand_{it} + \beta_2 Mand_{it} + \beta_3 Controls_{it} + \beta_4 State_i + \beta_5 Year_t \\ &+ \beta_6 (State_i * Year_t) + u_{it} \end{aligned} \tag{2}$$

$Mand_{it}$ indicates whether state i has adopted a mandatory PDMP in period t. The coefficient of interest is β_2, which measures the average post-treatment effect of adopting the relevant mandatory PDMP on prescription rates. All other variables are as in (1). The validity of (2) relies on the assumption that non-treated and treated states follow parallel trends prior to treatment, which is presumably unlikely to hold for all 23 states that are treated between 2006 and 2017.

For this reason, I also estimate (2) using the Synthetic Control Method (SCM) following Abadie et. al (2015), which relaxes the parallel trends assumption. Unlike DD models, the synthetic control model uses a subset of units as controls for comparison (as opposed to all states). This method selects control states that exhibit the same pre-treatment dynamics as the treated states of interest. The SCM also allows us to determine dynamic treatment effects.

3.2 Synthetic Control Method

Let Y_{st} be the outcome of interest for unit s of $S+1$ state units at time $t \in (1,...,T)$. Assume that the sample contains a positive number of pre-treatment periods, T_0, and a positive number of post-treatment periods, T_1, where $T = T_0 + T_1$. Let the treated state, $s = 1$, be exposed to the intervention during $T_0 + 1,...,T$. The synthetic control estimator models the effect of the mandatory PDMP policy at time $t \in (T_0 + 1,...,T)$ on the treatment group using a linear combination of optimally chosen states as a synthetic control. That is, a synthetic control can be represented by an $(Sx1)$ vector of weights $W = (w_2,...,w_{S+1})$ where $0 \leq w_s \leq 1$ for all $s \in (2,...,S+1)$ and $w_2 + ... + w_{S+1} = 1$. These weights are selected such that they minimize the root mean squared predicted error (RMSPE) pre-treatment, and then are applied to the outcome of interest ex post. The synthetic control estimator measures the causal effect as $Y_{1t} - \sum_{s=2}^{S+1} w_{s^*} * Y_{st}$.

The gsynth package in R (Xu 2017) imputes counterfactuals for each treated unit using control group information based on a linear interactive fixed effects model that incorporates unit-specific intercepts interacted with time-varying coefficients. It generalizes the synthetic control method to the case of multiple treated units and variable treatment periods and allows the treatment to be correlated with unobserved unit and time heterogeneities. With a built-in cross-validation procedure, it avoids specification searches and thus is easy to implement. The specification is as in (2), but I omit the $State_i * Year_t$ interaction term as it is unnecessary for the Synthetic Control.

I also estimate (2) using the SCM with the gsynth package, where the dependent variable Y_{it} is total inpatient stays per 100,000 population, stays by age group, income quartile, and metro area. Further, I also estimate these for emergency department uses per 100,000 population.

Lastly, I estimate (2) using the SCM where Y_{it} is total NAS hospitalizations per 1,000 newborn hospitalizations, as well as rate by expected payer, income quartile, and metro area. In these regressions, I control for the same state-level laws, unemployment rates, alcoholic tax rates, percent covered by insurance, and per capita personal income, all of which could plausibly impact drug consumption and hence hospital use and NAS rates

both before and after treatment.

4 Results

4.1 Preliminary analysis

Average prescription rates are shown in Table 1 for states that implemented mandatory PDMPs in 2012 and states that are never treated. It is evident that these states tend to have higher prescription rates than the average of never-treated states, but these rates substantially decrease after 2012.

Table 2 shows the average number of opioid-related inpatient stays per 100,000 population by demographic group. Evidently, inpatient stays are highest for those ages 25-44, appear to be more concentrated in medium metro areas, lower income quartiles, and are slightly higher for women than for men. Average emergency department inpatient stays per 100,000 population are in Table 3. Surprisingly, these rates are highest for those ages 45-64, in medium metro areas, lower income quartiles, and are higher for men than women.

Average NAS rates are shown in Table 4. Notably, these averages are drastically higher for Medicaid patients than for those on private insurance, and higher still than those without insurance. Rates are higher on average in small and medium metro areas, and are higher in lower income quartiles, as expected based on previous findings.

4.2 Regression Results

Table 5 shows results from (1). The significance of pre-treatment coefficients weakens the parallel trends assumption and the results from column 1. The SCM can mitigate potential bias in these results. Estimations on the subset of all treated states, shown in Table 6, show significant early-stage post-treatment effects of about 5 percent, and later post-treatment effects as high as 20 percent, on average. The average post-treatment effect is a decrease of 6.21 prescriptions per 100 persons in states that implement a mandatory PDMP, as compared to those that do not. These results do not greatly change when run on a subset

of treated states with at least 3 post-treatment periods (Tables 8 and 9), and increase when run on a balanced panel of states all of which have 6 post-treatment periods, yielding a post-treatment decrease by 20 percent after 6 periods of treatment, and an average post-treatment effect of 13 prescriptions per 100 persons (Tables 10 and 11). Figures 2 and 4, which show the estimated fit of treated and control counterfactuals, give strong confidence to these results.

While results in Table 12 suggest that inpatient stays are decreasing in treated states, these results are insignificant, as are all sub-categories of inpatient stays. Estimations on emergency department visits are problematic due to lack of reporting and missing data across many states. Since all subsets on balanced panels are extremely small, it is difficult to obtain any informative estimates of changes in opioid-related emergency department visits on average and across demographic groups.

Estimations on the NAS data are more surprising. Table 16 estimates the SCM on NAS rates including all treated states. While these results are not significant, substantial changes in the composition of treated states in each post-treatment period may be altering these results. For this reason, I estimate these on a balanced panel, including states with at least 6 post-treatment periods, shown in Table 18. The states included in this treatment group are also included in the results shown in Table 10. NAS rates post-treatment are increasing over time, with increases as high as 10 newborns per 1,000 hospitalizations after 6 post-treatment periods, and an average of 5 newborns per 1,000 hospitalizations. Table 21 shows that these increases are even more drastic in the Medicaid population, with increases as large as 20 newborns per 1,000 hospitalizations, and an average post-treatment effect of 12 newborns per 1,000 hospitalizations. While estimates on the self-pay population are insignificant, estimates on the private-insurance subgroup are. The estimates in Table 26 show increases of about 2 NAS diagnoses per 1,000 newborns, far less than estimates reported for the Medicaid population. Figures 7-13, which show fitted treated and control counterfactuals from the SCM, give confidence to these results.

Estimates of NAS rates for patients in the highest income quartile were also significant. As shown in Table 29, NAS rates increased for patients in the fourth income quartile by roughly 3 births per 1,000 population. Due to technological issues, I was not able to run

these on a fully balanced panel.

5 Discussion

Mandatory PDMPs are associated with significant reductions in opioid prescription rates, as large as 20 percent after several periods of treatment. While other authors have found evidence of reductions in measures of doctor shopping, it is important that researchers carefully consider their sources for PDMP implementation dates, as researchers have shown that differences in commonly used sources account for large discrepancies in results. Unfortunately, due to data limitations, it is unclear exactly for whom doctors are restricting prescriptions. They may be more prone to inspecting records more closely for some patients than others, or patients themselves from certain groups may be more easily deterred from doctor shopping than others. Further work is needed to more closely examine prescription rate trends by demographic group.

I did not find any significant results with respect to hospital use. Better quality emergency room data could be useful in determining which demographic groups are particularly responsive to supply shocks of prescription opioids. Results from Bachmueller (2018) suggest that while many in the Medicare population reduce their shopping behavior, opioid poisonings do not significantly diminish. These results could suggest that low income adults may be more likely to substitute towards other drugs when prescription drugs are harder to obtain, but further study is needed to evaluate whether this hypothesis holds up when using the correct PDMP implementation dates.

The NAS results are more striking. While increases in NAS rates post-treatment are small, they are significant not only among the Medicaid population, but also among the privately insured in states with several post-treatment periods who also exhibit substantial decreases in opioid prescription rates. The significant increases in the Medicaid population of up to 2 percent (after 6 periods of treatment) are alarming, given the higher associated costs and lengths of stays with Medicaid-insured NAS newborns.

It is possible that doctors are not as responsive to these policies when it comes to pregnant women in general, who may be dealing with pain for several months, than they

are for young men. While the increases in NAS rates are more pronounced for Medicaid patients, the small but significant increases that are prevalent for women on private insurance and with higher incomes, also speaks to the possibility of this issue.

Additionally, it may also be the case that women on Medicaid are more likely than their high-income counterparts to engage in behavior that can exacerbate the likelihood of giving birth to a baby with NAS, such as smoking cigarettes or taking SSRIs. If Medicaid women were transitioning to more dangerous drugs like heroin or cocaine, then to the extent that doctors are able to recognize these symptoms at the time of birth, it is more likely to observe increases in diagnosis rates of withdrawal associated with these drugs, rather than in the NAS diagnosis category that I analyze. Unfortunately, I do not have access to data that specifies these diagnoses. In order to better analyze this issue, further study would consider data on the mother-level, which would include a specific substance-related diagnosis for the mother herself (including cigarette and SSRI use) as well as a diagnosis for the newborn. Additionally, if we expect that most of these mothers are women who begin taking opioids to manage pain during their first pregnancy, and either increase opioid use or transition to substances that exacerbate the likelihood of NAS, then second or later-born children may be more likely to be born with NAS than the first-born child. Again, data at the mother level that indicates birth-order would be useful in considering this issue.

Since not all patients in the sample are necessarily included in an insurance category, it is hard to compare any results for Medicaid, privately insured, or high-income women to the average increases, of about .5%.

Although mandatory PDMPs are a successful intervention from a supply perspective, these policies do not necessarily elicit the same responses from all groups. While other studies have shown significant decreases in abuse measures and crime for young adult males, studying womens' responses to these policies are important, as both high and low-income women are using opioids during pregnancy, leading to costly and devastating outcomes for hospitals and newborns. Policymakers must also consider relevant demand-side interventions for pregnant women in terms of managing pain, particularly for low-income patients, who may turn to destructive, perhaps less costly routes of pain relief

when prescription opioids become harder to obtain.

6 Conclusion

I contribute to the current literature relating to mandatory PDMPs by estimating the effects of these policies on opioid prescription rates, hospital use rates, and NAS rates. I find that mandatory PDMPs reduce state-level opioid prescription rates by 13% on average, and these decreases grow over time. Further, while I find no conclusive evidence of changes in hospital use rates, either in inpatient or emergency department discharges related to opioid use, I find significant increases in NAS rates, of 5 per 1,000 newborn hospitalizations on average. Substantial increases are evident for mothers insured under Medicaid, with increases of 12 per 1,000 newborn hospitalizations on average. Additionally, these mandatory policies are also associated with an increase of 1.8 cases per 1,000 newborn hospitalizations among privately insured mothers, and there is some weak evidence for increases among mothers in the highest income quartile. These results speak to the necessity for policymakers to not only address the opioid epidemic through supply-side interventions, but also through adaptive demand-side policies.

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Table 1: Average Opioid Prescription Rate Across States Treated in 2012

year	DE	KY	NM	WV	Never-Treated States
2006	86.60	122.60	61.80	129.90	71.72
2007	92.30	130.80	69.00	135.10	74.74
2008	95.40	136.60	71.40	145.50	77.03
2009	97.50	135.20	75.30	146.90	77.96
2010	101.10	136.50	81.90	143.10	79.92
2011	99.70	137.00	81.60	139.60	79.76
2012	94.00	127.90	76.80	136.90	80.91
2013	92.70	111.70	71.40	129.00	78.49
2014	91.00	110.00	71.50	126.40	76.56
2015	84.40	102.60	69.80	111.30	71.42
2016	79.20	97.20	65.10	96.00	67.34
2017	68.30	86.80	56.40	81.30	59.91

Table 2: Average Opioid-Related Inpatient Stays per 100,000 Population

Total	<1 year	1-24 years	25-44 years	45-64 years	ages 65+
210.12	42.76	67.09	303.86	284.51	242.88

rural	small urban	medium metro	large fringe metro	large metro
194.02	201.46	213.81	198.55	165.58

income quartile 1	income quartile 2	income quartile 3	income quartile 4	female	male
216.88	228.25	181.95	134.41	214.86	205.51

Table 3: Average Opioid-Related Emergency Department stays per 100,000 Population

Total	<1 year	1-24 years	25-44 years	45-64 years	ages 65+
155.82	5.60	88.64	144.23	154.01	62.92

rural	small urban	medium metro	large fringe metro	large metro
156.41	147.46	167.68	158.14	105.57

income quartile 1	income quartile 2	income quartile 3	income quartile 4	female	male
141.58	180.46	138.52	98.88	139.44	172.98

Table 4: Number of Babies Born with NAS per 1,000 Newborn Hospitalizations

Total	Females born	Males born
7.08	6.78	7.36

Medicaid	Private Insurance	Self-Pay
13.09	1.63	8.90

rural	small urban	medium metro	large fringe metro	large metro
7.70	8.37	7.73	6.36	5.25

income quartile 1	income quartile 2	income quartile 3	income quartile 4
9.48	7.63	6.10	4.25

Table 5: Prescription Rate Diff-in-Diff Results

	(1)	(2)	(3)	(4)
Non-Mandatory PDMP	0.060	0.538	0.534	0.495
	(1.746)	(1.469)	(1.466)	(1.658)
Mandatory PDMP	-7.208***			
	(1.592)			
T = -3		5.458***	5.458***	4.583***
		(1.289)	(1.289)	(1.181)
T = -2		5.694***	4.890***	3.932***
		(1.089)	(0.941)	(0.828)
T = -1		4.891***	4.168***	3.684***
		(1.216)	(1.154)	(1.097)
T = 1		-1.143	-1.869	-0.032
		(1.868)	(1.893)	(1.801)
T = 2		-3.183	-3.927	-1.095
		(2.505)	(2.569)	(2.704)
T =3		-3.743	-4.494*	-0.591
		(2.530)	(2.623)	(2.463)
Obs.	564	564	564	564
R-squared	0.750	0.591	0.577	0.741
State-Specific Trends	YES	NO	NO	YES
Controls	YES	YES	YES	YES

Standard errors are in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Prescription Rate Results

T	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-3	0.305	0.445	-0.373	1.231	0.430	0
-2	0.313	0.455	-0.429	1.268	0.440	0
-1	0.226	0.356	-0.434	0.946	0.590	0
0	-0.656	0.667	-1.998	0.478	0.350	0
1	-3.210**	1.311	-5.720	-0.415	0.020	22
2	-5.559***	1.943	-8.875	-1.053	0	17
3	-5.560*	2.701	-9.928	0.098	0.080	15
4	-7.232	4.595	-14.808	4.144	0.130	10
5	-8.487	6.468	-19.169	7.672	0.170	8
6	-20.832**	8.159	-32.007	-0.086	0.050	4

Table 7: Prescription Rate Results Average Treatment Effect

ATT.avg	S.E.	CI.lower	CI.upper	p.value
-6.211**	2.594	-9.494	-0.582	0.040

Table 8: Prescription Rate Results (Treated States with at least 3 Post-Treatment Periods)

T	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-3	0.263	0.357	-0.396	0.938	0.430	0
-2	0.469	0.561	-0.591	1.590	0.410	0
-1	0.277	0.444	-0.655	1.101	0.450	0
0	-0.740	0.695	-2.133	0.373	0.240	0
1	-3.410*	1.475	-6.279	-0.683	0.010	15
2	-5.762*	2.145	-10.176	-2.309	0.010	15
3	-5.560**	2.608	-10.578	-0.648	0.050	15
4	-7.232	4.464	-14.513	1.996	0.120	10
5	-8.487	6.641	-18.865	5.881	0.190	8
6	-20.832**	10.859	-33.321	-5.054	0.030	4

Table 9: Average Treatment Effect Prescription Rates (Treated States with At least 3 Post-Treatment Periods

ATT.avg	S.E.	CI.lower	CI.upper	p.value
-6.635*	3.043	-10.608	0.019	0.060

Table 10: Prescription Rate Results (Treated States with 6 Post-Treat Periods)

T	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-3	0.093	0.881	-1.215	2.387	0.890	0
-2	-0.104	0.586	-1.350	1.065	0.910	0
-1	-0.005	0.943	-1.847	1.559	1	0
0	0.017	0.513	-1.202	0.705	0.900	0
1	-6.146*	3.431	-11.355	3.111	0.100	4
2	-11.184*	4.655	-18.856	1.129	0.060	4
3	-10.494*	4.861	-17.612	3.156	0.070	4
4	-13.081**	4.603	-20.327	-3.219	0.030	4
5	-16.984**	5.404	-24.861	-4.615	0.030	4
6	-20.832**	6.701	-29.639	-3.881	0.040	4

Table 11: Average Treatment Effect Prescription Rates (Treated States with 6 Post-treatment periods)

ATT.avg	S.E.	CI.lower	CI.upper	p.value
-13.120**	4.312	-20.721	-2.287	0.020

Table 12: Hospital Inpatient Stays (Treated States With 6 Post-Treat Periods)

T	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-3	-1.912	9.556	-26.702	6.275	0.470	0
-2	-3.416	8.581	-21.927	11.052	0.540	0
-1	7.548	7.441	-10.270	18.399	0.360	0
0	-2.220	10.103	-5.974	30.949	0.670	0
1	-43.847	39.627	-71.231	47.923	0.400	3
2	-85.721	72.446	-161.460	121.316	0.450	3
3	-104.614	82.720	-182.407	114.848	0.410	3
4	-181.926	143.696	-330.037	228.076	0.390	3
5	-188.197	169.220	-398.983	312.344	0.460	3
6	-161.292	168.914	-354.821	329.929	0.530	3

Table 13: Hosp Inpatient 6 post-treat Average Treatment Effect

ATT.avg	S.E.	CI.lower	CI.upper	p.value
-127.600	107.786	-225.153	176.422	0.450

Table 14: Emergency Department Results (All Treated States)

	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-3	-0.828	7.199	-15.483	4.983	0.500	0
-2	-5.070	7.405	-10.555	7.798	0.460	0
-1	2.844	10.285	-12.308	17.506	0.710	0
0	-0.226	8.372	-4.904	25.444	0.590	0
1	6.401	21.422	-25.250	58.341	0.590	13
2	0.721	39.646	-61.107	87.862	0.620	9
3	7.356	71.459	-102.210	137.854	0.560	8
4	9.825	95.317	-132.460	173.161	0.480	6
5	77.913	161.468	-190.035	301.165	0.390	2
6	98.519	261.921	-137.941	338.846	0.222	1

Table 15: Average Treatment Effect Emergency Department (All Treated States)

ATT.avg	S.E.	CI.lower	CI.upper	p.value
11.842	53.867	-60.777	105.297	0.470

Table 16: NAS Rates (All Treated States)

T	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-3	0.516	0.250	0.060	0.975	0.040	0
-2	0.128	0.212	-.226	0.632	0.530	0
-1	-0.213	0.184	-0.518	0.254	0.190	0
0	-0.241	0.265	-0.651	.384	0.570	0
1	-0.287	0.627	-1.408	1.215	0.860	20
2	0.654	1.046	-1.285	2.777	0.560	15
3	0.314	1.358	-1.745	3.224	0.620	14
4	1.206	2.535	-4.155	4.749	0.840	9
5	8.396*	5.266	-7.587	12.374	0.730	6
6	10.707	7.734	-6.141	26.264	0.090	3

Table 17: Average Treatment Effect NAS (All Treated States)

ATT.avg	S.E.	CI.lower	CI.upper	p.value
0.799	1.738	-2.960	3.603	0.450

Table 18: NAS Rates (States with 6 Post-Treatment Periods)

T	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-3	0.340	0.316	-0.851	0.604	0.330	0
-2	-0.252	0.400	-1.099	0.401	0.520	0
-1	-0.463	0.343	-0.984	0.278	0.280	0
0	0.376	0.326	-0.044	1.091	0.080	0
1	0.470	1.592	-1.510	3.689	0.490	3
2	3.419	3.354	-1.293	10.595	0.160	3
3	4.544**	3.156	0.921	13.460	0.030	3
4	5.192**	3.574	0.849	14.761	0.040	3
5	8.396*	4.716	1.851	21.287	0.010	3
6	10.707*	6.272	1.594	26.636	0.010	3

Table 19: Average Treatment Effect (States with 6 Post-Treatment Periods)

ATT.avg	S.E.	CI.lower	CI.upper	p.value
5.455**	3.569	0.661	15.233	0.020

Table 20: NAS Results for Mothers on Medicaid

T	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-3	0.819	0.601	-0.447	1.881	0.260	0
-2	0.187	0.528	-0.628	1.339	0.790	0
-1	-0.165	0.464	-0.668	1.227	0.940	0
0	-0.332	0.634	-0.973	1.573	0.990	0
1	-0.369	1.561	-2.706	4.023	0.960	19
2	0.802	3.077	-4.679	9.089	0.580	14
3	0.980	5.087	-10.197	10.764	0.660	13
4	-1.220	8.767	-18.670	14.782	0.960	9
5	-1.045	14.677	-28.603	34.879	0.890	6
6	20.276	15.833	-13.916	50.366	0.190	3

Table 21: NAS Results for Mothers on Medicaid (Treated States with 6 Post-Treat Periods

T	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-3	0.385	0.844	-2.106	1.097	0.760	0
-2	-0.170	0.642	-1.243	1.363	0.850	0
-1	-0.816	0.531	-1.504	0.611	0.140	0
0	0.601**	0.581	0.026	2.371	0.050	0
1	2.496	2.584	-1.073	8.513	0.200	3
2	7.571*	5.650	-1.317	20.080	0.100	3
3	11.510**	7.062	1.084	27.990	0.040	3
4	13.005*	9.148	-0.025	33.076	0.060	3
5	17.069*	11.624	-1.220	41.050	0.070	3
6	20.276	15.628	-8.005	50.019	0.110	3

Table 22: Average Treatment Effect NAS for Mothers on Medicaid (Treated States with 6 Post-Treat Periods)

ATT.avg	S.E.	CI.lower	CI.upper	p.value
11.988*	8.672	-4.448	27.354	0.080

Table 23: NAs Results Mother on Private Insurance (All Treated States)

T	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-3	-0.077	0.093	-0.282	0.084	0.310	0
-2	0.141	0.099	-0.051	0.317	0.160	0
-1	-0.146	0.139	-0.373	0.229	0.250	0
0	0.230	0.175	-0.045	0.610	0.140	0
1	0.367	0.361	-0.122	1.187	0.200	19
2	0.654*	0.450	-0.025	1.645	0.080	14
3	0.833**	0.469	0.025	1.944	0.040	13
4	1.245**	0.651	0.296	2.736	0.030	9
5	1.392*	0.787	0.192	2.938	0.010	6
6	2.385**	1.341	0.150	5.363	0.020	3

Table 24: Average Treatment Effect NAS Mothers on Private Insurance (All Treated States)

ATT.avg	S.E.	CI.lower	CI.upper	p.value
0.839***	0.427	0.170	1.808	0

Table 25: NAS Results Mothers on Private Insurance (Treated States with 6 Post-Treat Periods)

T	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-3	0.189	0.240	-0.297	0.544	0.610	0
-2	0.366	0.371	-0.601	0.925	0.450	0
-1	-0.779	0.200	-1.078	-0.366	0	0
0	0.337	0.233	0.046	0.913	0.020	0
1	0.128	0.493	-0.428	1.226	0.470	3
2	1.267	1.720	-0.781	5.240	0.570	3
3	2.403***	1.328	0.843	5.452	0	3
4	2.254*	1.281	0.550	5.256	0.010	3
5	2.427***	1.135	0.906	5.160	0	3
6	2.692***	1.438	1.017	5.732	0	3

Table 26: Average Treatment Effect NAS Mothers on Private Insurance (Treated States with 6 Post-Treat Periods)

ATT.avg	S.E.	CI.lower	CI.upper	p.value
1.862***	1.116	0.588	4.523	0

Table 27: NAS Results Income Quartile 4

T	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-3	-0.032	0.549	-1.071	1.048	0.980	0
-2	-0.470	0.583	-1.804	0.488	0.360	0
-1	1.084	0.830	-0.443	2.703	0.140	0
0	0.346	0.380	-0.290	1.211	0.400	0
1	1.354	0.754	-0.332	2.584	0.130	14
2	1.437**	0.877	-0.120	3.130	0.080	14
3	2.436***	0.949	0.638	4.186	0.010	14
4	2.464*	1.733	-0.436	6.167	0.100	9
5	5.181*	4.109	-0.412	14.117	0.080	6
6	10.043	7.173	-1.411	24.157	0.240	3

Table 28: NAS Results Income Quartile 4 (Treated States 6 Post-Treatment Periods)

T	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-3	0.014	1.003	-1.703	2.051	1	0
-2	-1.586	1.088	-3.733	0.505	0.130	0
-1	1.970	1.503	-1.117	4.749	0.160	0
0	0.348	0.600	-0.757	1.533	0.620	0
1	1.788	1.223	-0.483	4.052	0.180	7
2	2.692**	1.578	0.260	6.015	0.020	7
3	3.768**	1.529	0.885	6.704	0.020	7
4	2.732	2.071	-1.653	6.790	0.190	7
5	5.181*	3.528	-0.041	12.760	0.060	6
6	10.043	7.131	-0.983	25.202	0.150	3

Table 29: Average Treatment Effect NAS Income Quartile 4 (Treated States 6 Post-Treat Periods

ATT.avg	S.E.	CI.lower	CI.upper	p.value
3.732***	1.397	1.482	6.700	0

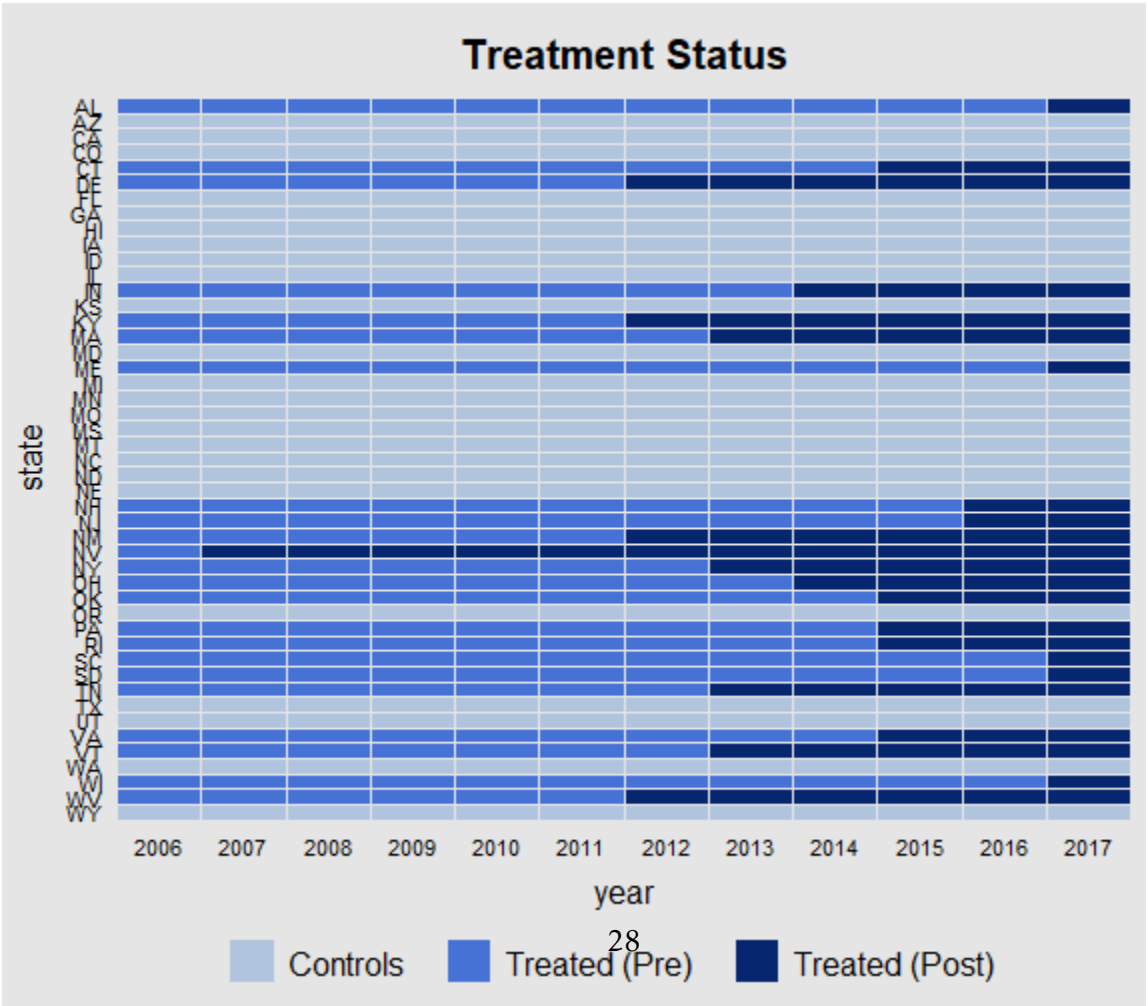

Figure 1: States in the Prescription Rate Sample (2006-2017)

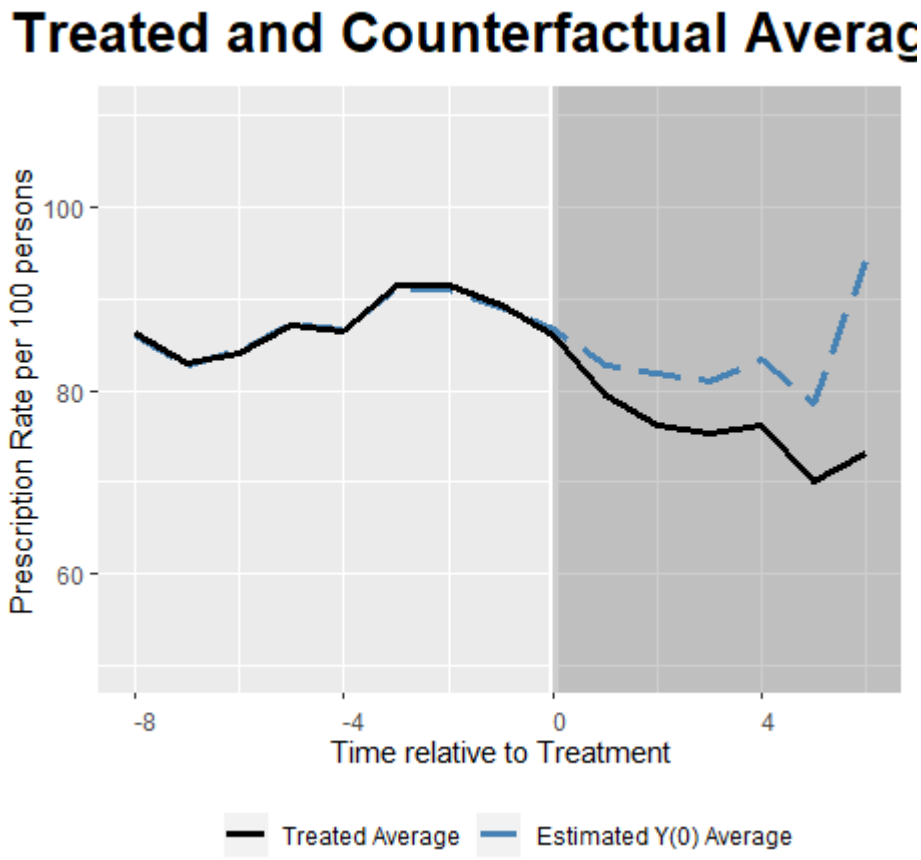

Figure 2: Synthetic Control Counterfactual (All Treated States)
(Corresponds to results in Table 6)

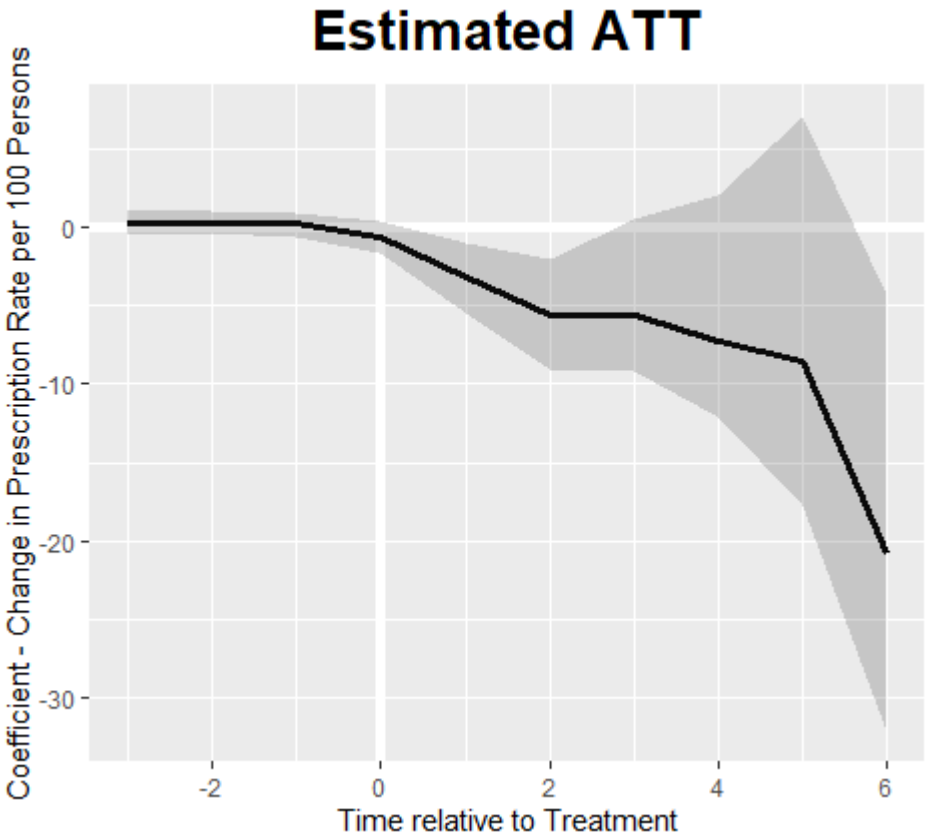

Figure 3: Average Treatment Effect (All Treated States)
(Corresponds to results in Table 6)

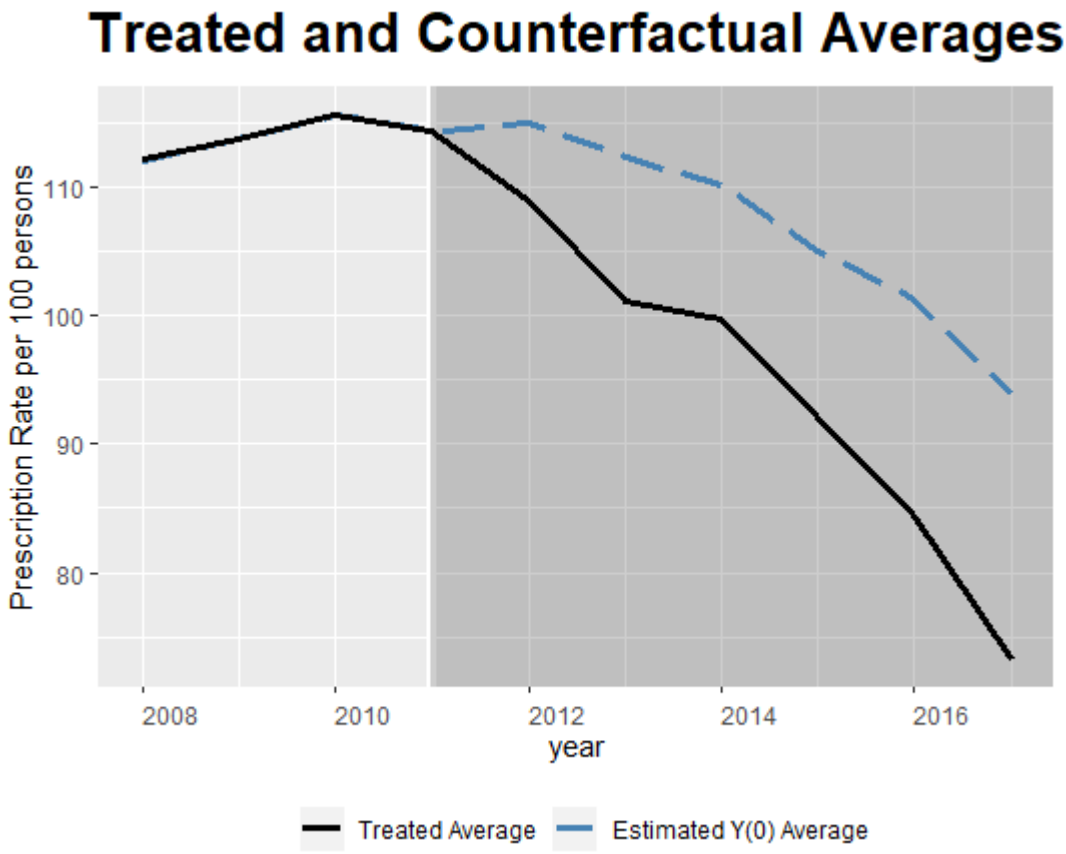

Figure 4: Synthetic Control Counterfactual (States with 6 post-treat Periods) (Corresponds to results in Table 8)

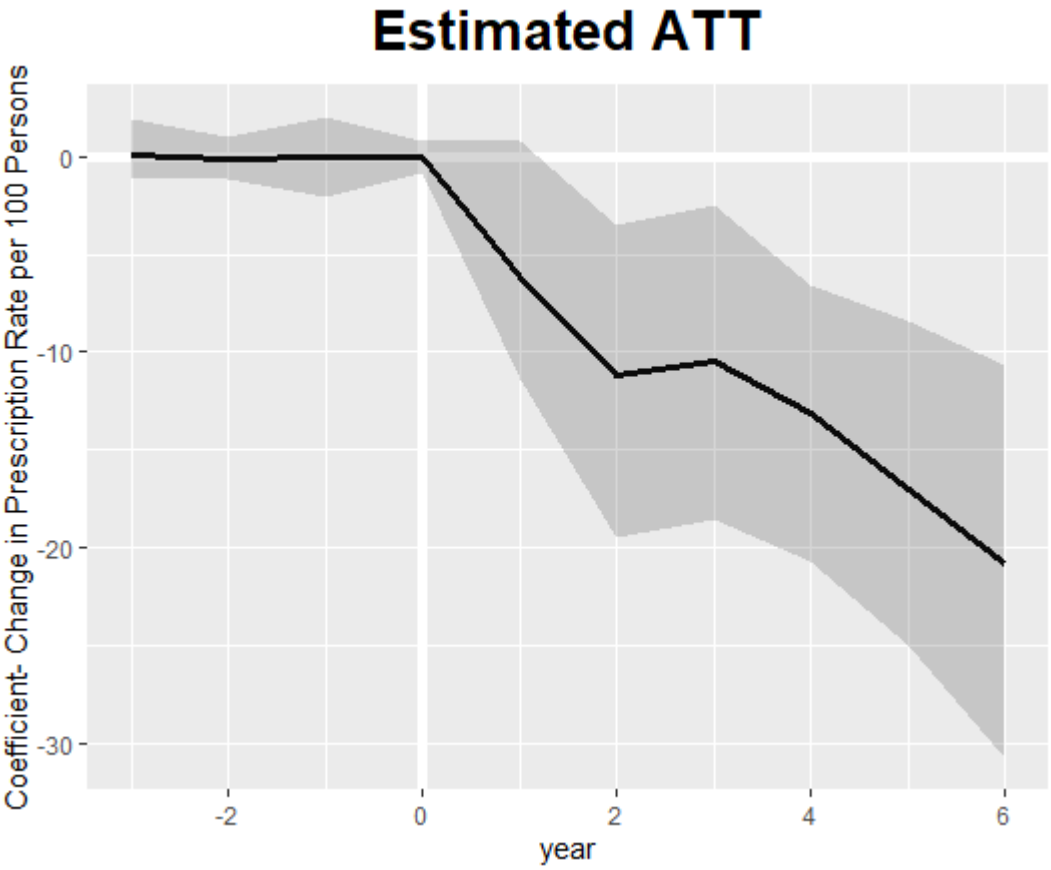

Figure 5: Estimated on States with 6 post-treat periods
(Corresponds to results in Table 8)

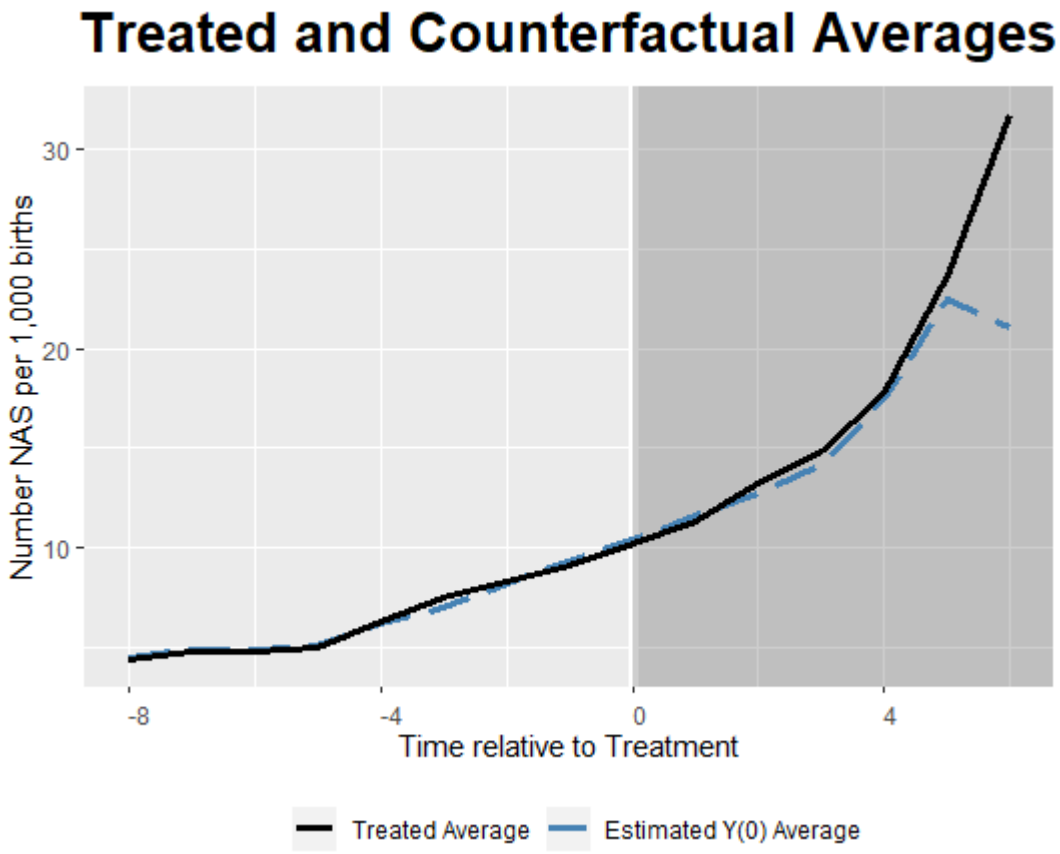

Figure 6: Synthetic Control Counterfactual (All Treated States)
Corresponds to Results in Table 13

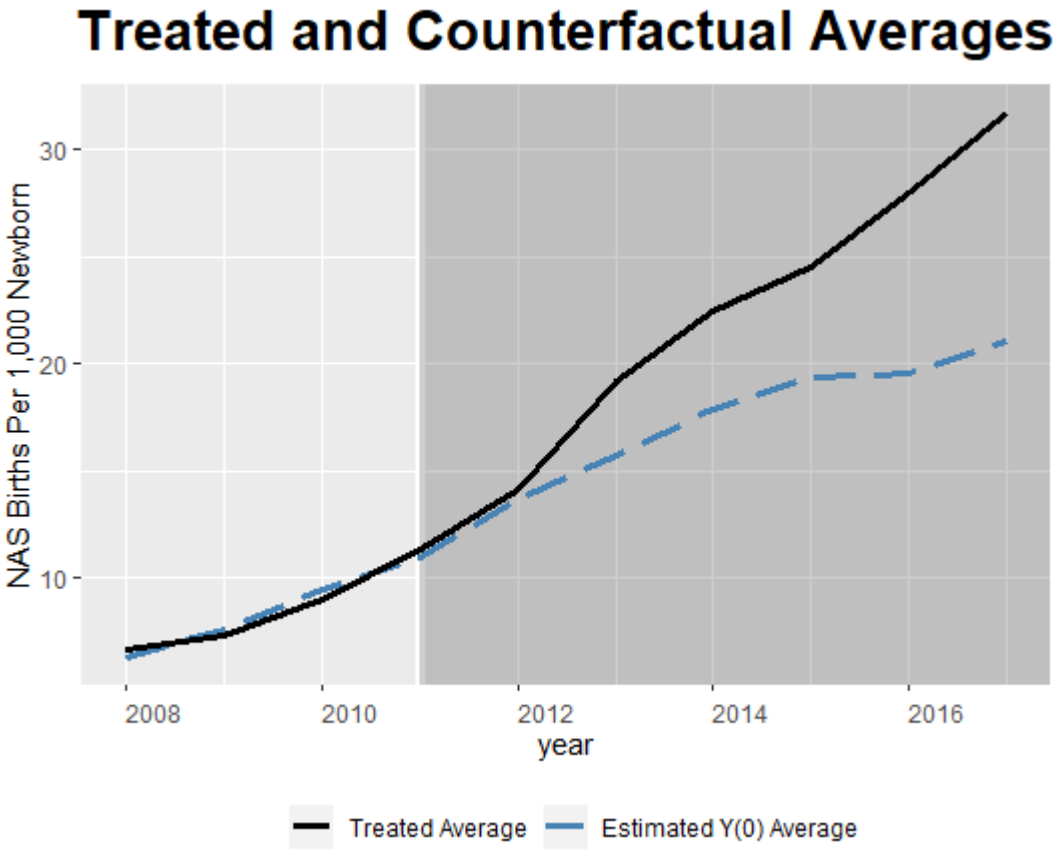

Figure 7: Synthetic Control Results (States with 6 Post-Treatment Periods) (Corresponds to Results in Table 15)

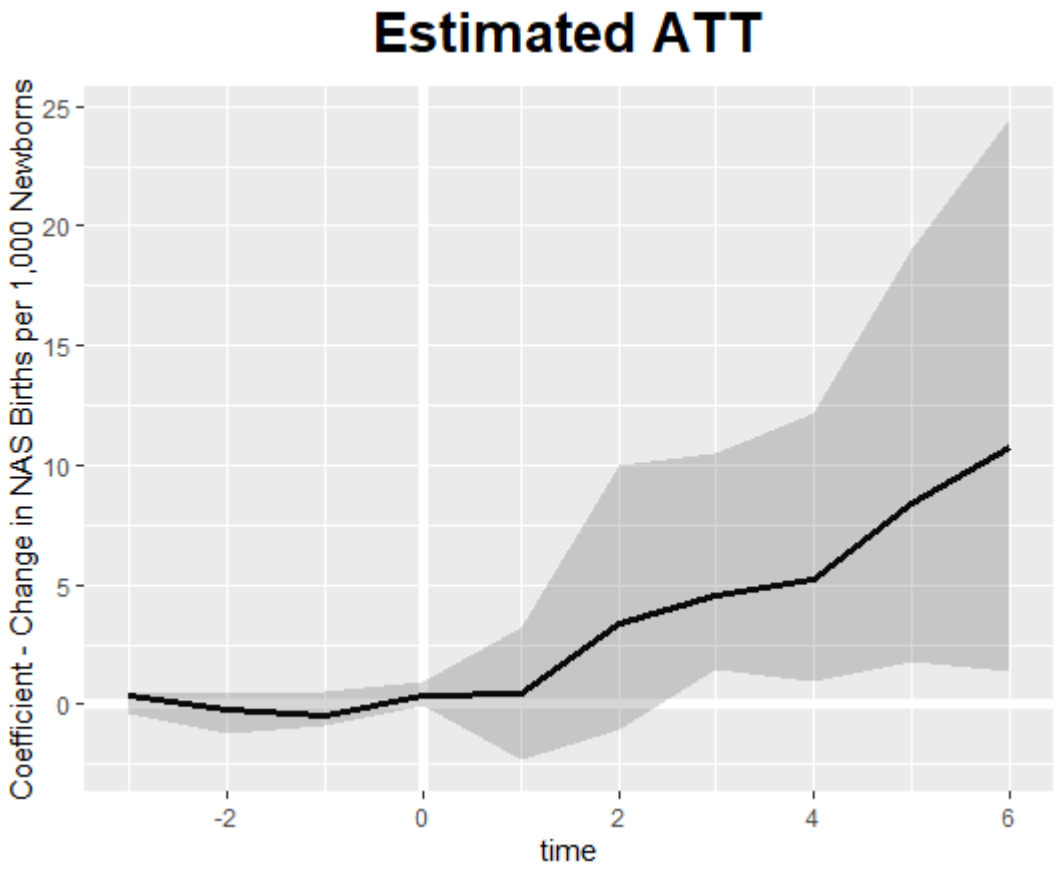

Figure 8 : Average Treatment Effect (States with 6 Post-Treatment Periods)
(Corresponds to Results in Table 15)

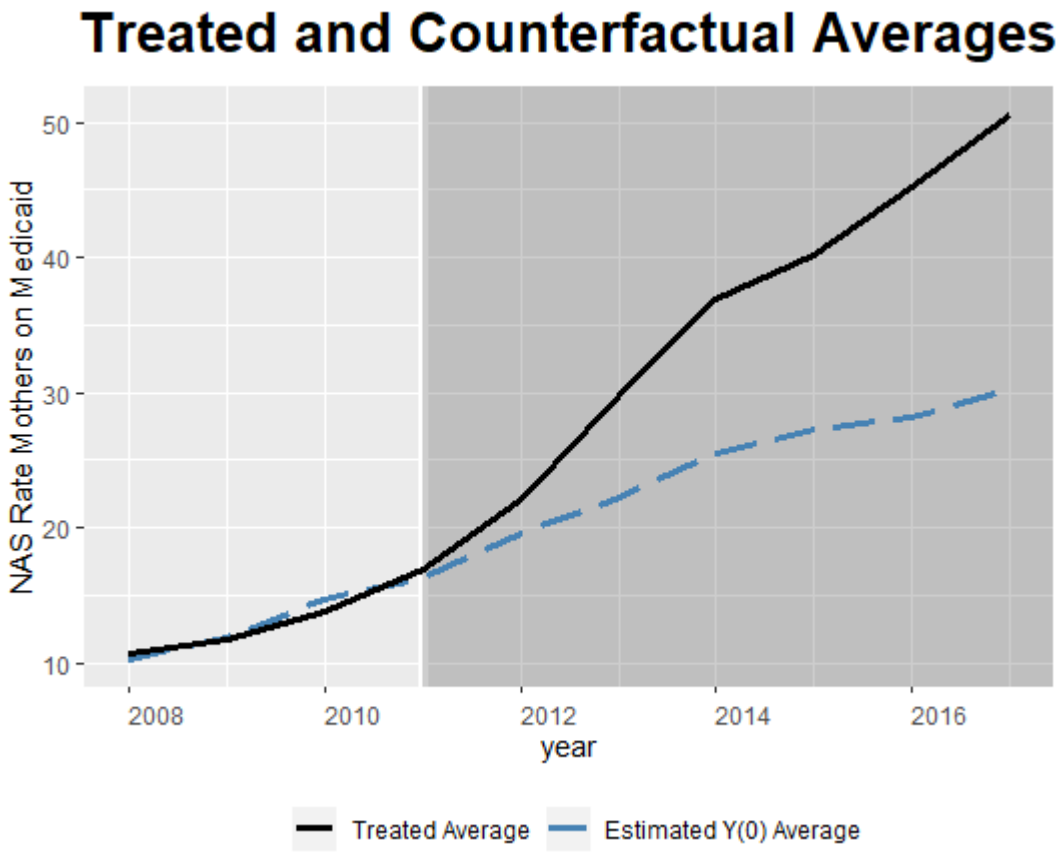

Figure 9: Synthetic Control Results (States with 6 Post-Treatment Periods) (Corresponds to results in Table 18)

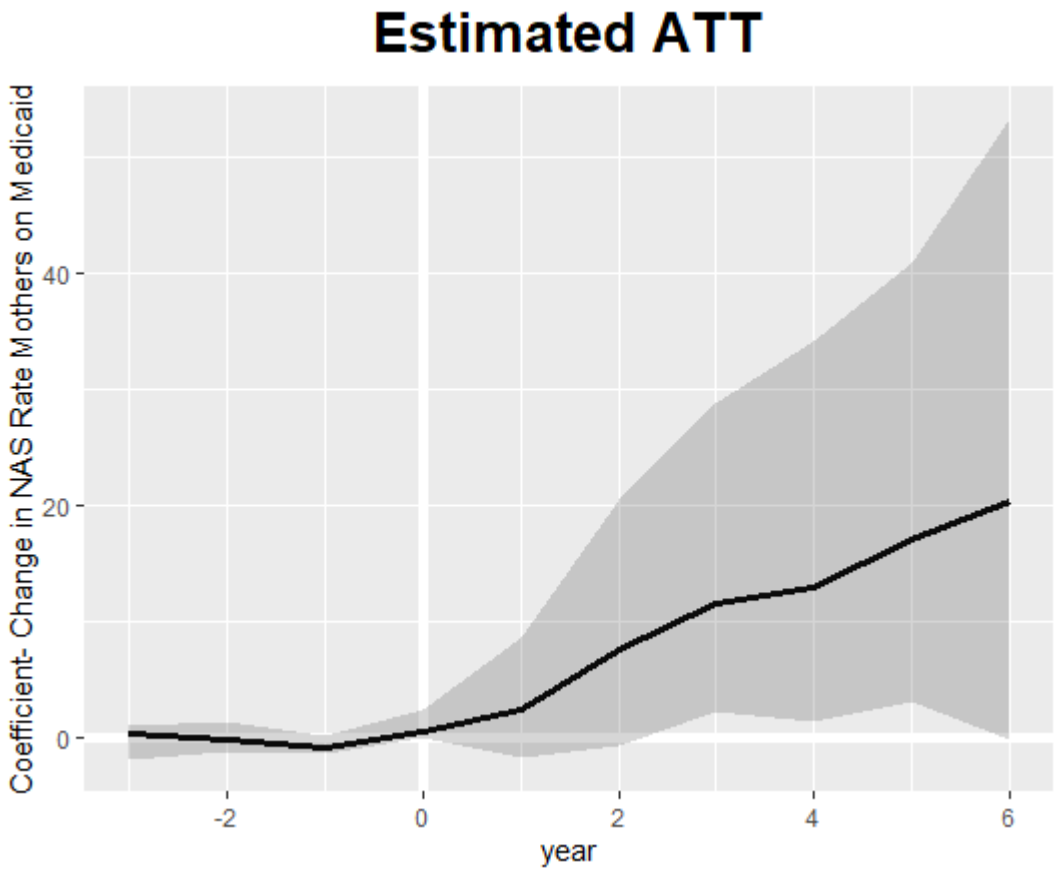

Figure 10: Average Treatment Effect (States with 6 Post-Treatment Periods) (Corresponds to results in Table 18)

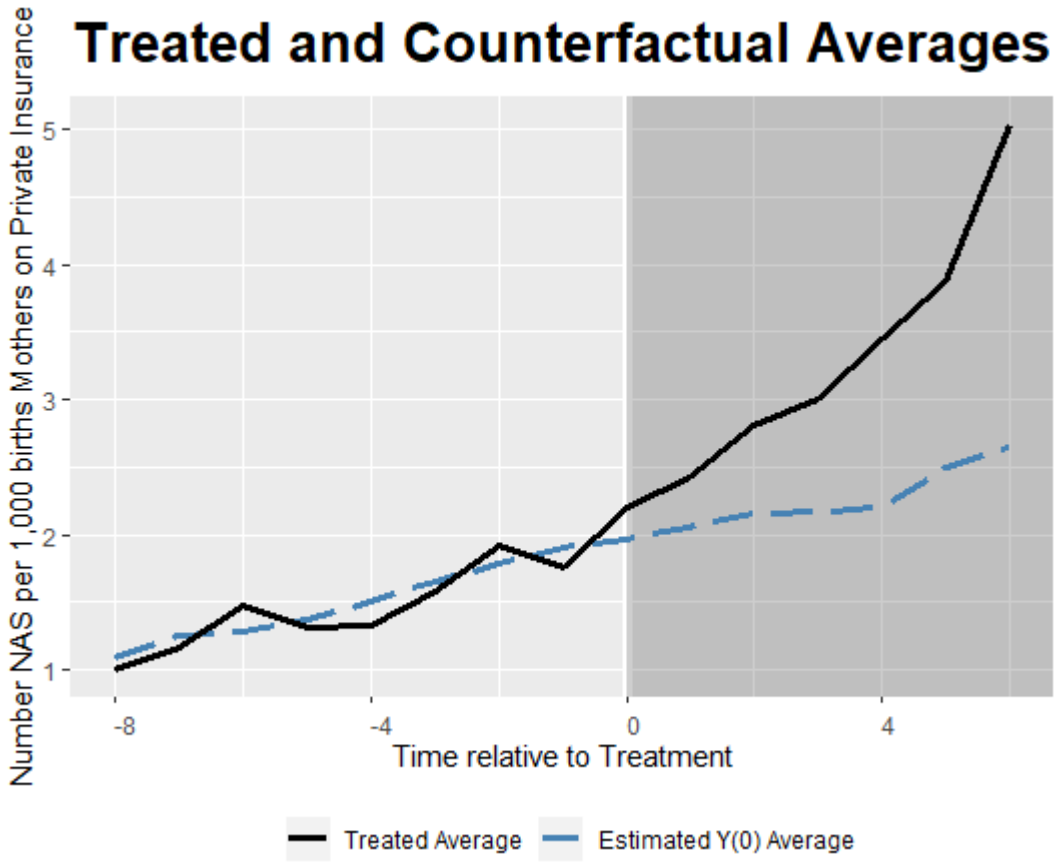

Figure 11: Synthetic Control Results (All Treated States)
(Corresponds to results in Table 20)

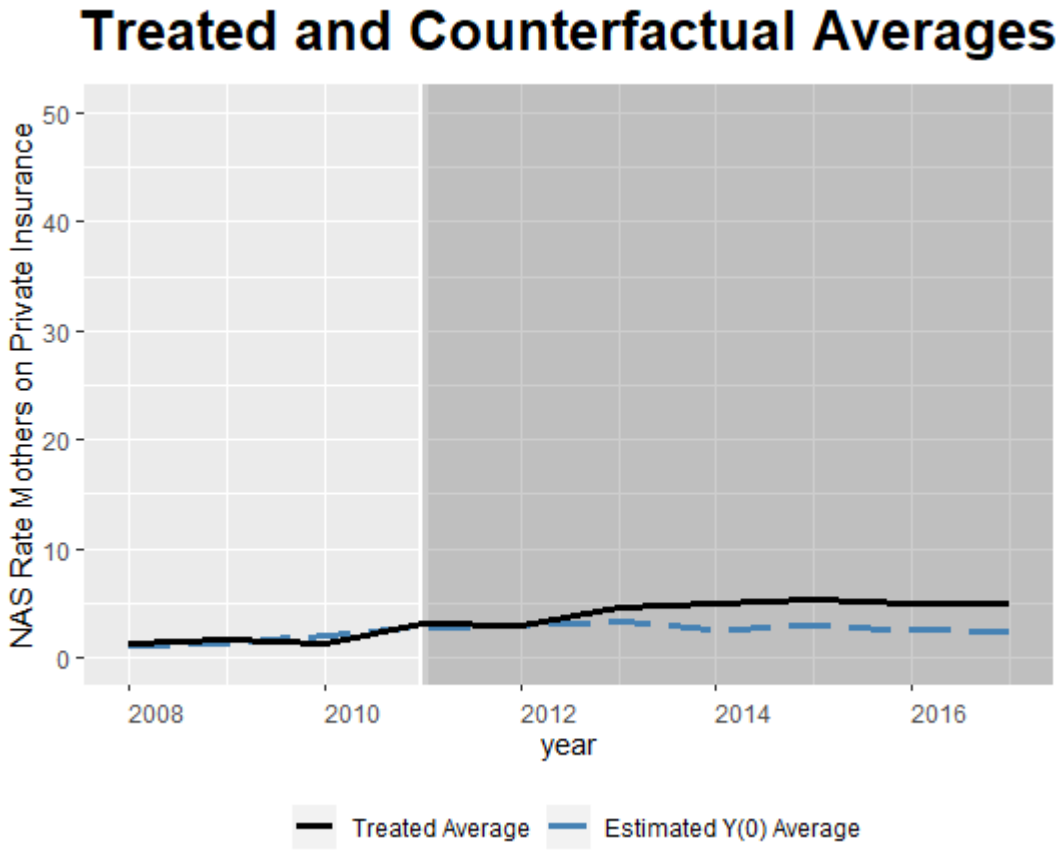

Figure 12: Synthetic Control Results (States with 6 Post-Treatment Periods) (Corresponds to results in Table 22)

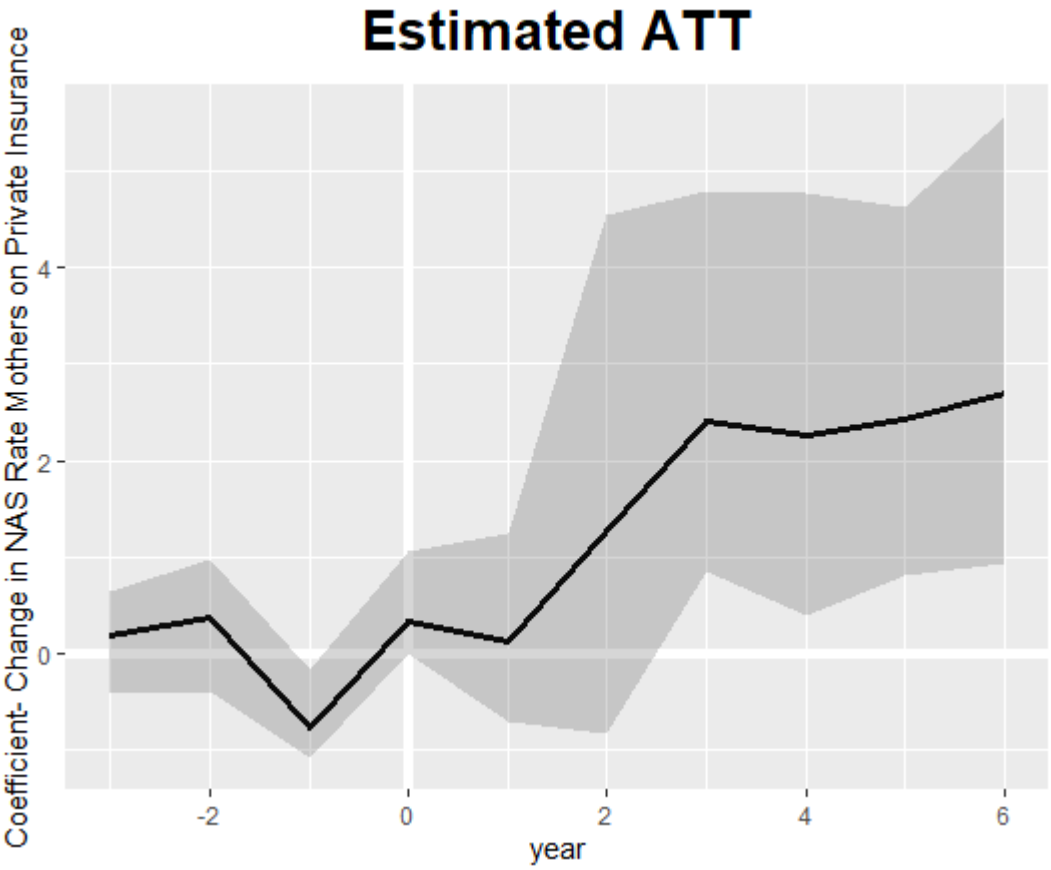

Figure 13: Average Treatment Effect (States with 6 Post-Treatment Periods) (Corresponds to Results in Table 22)