The Impact of Prescription Drug Monitoring Programs on Infant Health

Sidra Haye*

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Abstract

This paper examines the effect of Prescription Drug Monitoring Programs (PDMPs) on infant health outcomes. PDMPs are state databases that track prescribing and dispensing of controlled substances. To encourage database use, several states have adopted mandatory use policy that requires prescribers to consult these databases before prescribing. Using a difference-in-differences framework I find PDMPs and mandatory use policy have, at best, a very small impact on infant health outcomes. My results suggest that part of the mechanism underlying these results is substitution from prescription opioids to heroin.

JEL: I11, I12

Keywords: Opioids, Substance abuse, Infant Health

^{*}The University of California-Irvine, Department of Economics, 3151 Social Sciences Plaza, Irvine, CA (e-mail:shaye@uci.edu). I would like to thank Damon Clark, Mireille Jacobson, Matthew Freedman, Zarak Sohail, Shantanu Khanna and UCI Applied Microeconomics workshop participants for their excellent comments and feedback. Financial Support from UCI Summer Funding is acknowledged.

1 INTRODUCTION

Opioid misuse is a major health crisis in the United States; opioids were responsible for about 42,000 death in 2016 (CDC 2016). Opioid use during pregnancy has also increased rapidly in the last 20 years: opioid use disorder rates at delivery increased by 333 percent between 1999-2014 (Haight et al. 2018). Not surprisingly, this has contributed to an increased number of infants that experience opioid withdrawal syndrome- or neonatal abstinence syndrome- after birth (Patrick et al. 2012). Despite this, there is little empirical evidence on the effect of opioid crisis on a key predictor of adult outcomes: birth weight (Almond, Currie, and Duque 2017; Prinz et al. 2018).

In this paper, I explore the effect of Prescription Drug Monitoring Programs (PDMPs) on birth weight. These databases track prescribing and dispensing of controlled substances and have been widely introduced: only one state had an operational database with user access by 2000, but now forty-nine states have an operational database. While the earlier work on these databases finds mixed results (Meara et al. 2016; Meinhofer 2017; Paulozzi, Kilbourne, and Desai 2011; Bao et al. 2016; Radakrishnan 2013; Mallat 2017), recent work consistently finds that prescription opioid misuse declined in mandatory use states in which prescribers are required to consult PDMPs before prescribing under certain circumstances¹ (Buchmueller and Carey 2018; Grecu, Dave, and Saffer 2019; Ali, Dowd, Classen, Mutter, and Novak 2017). I build on this important literature by examining the effect of PDMPs on opioid use among reproductive age women and on infant health outcomes.

I use variation in timing of PDMPs and mandatory use policy adoption to estimate difference-in-differences models that compare outcomes in adopting states to outcomes in non-adopting states before and after policy adoption. I use the restricted use Vital Statistics Natality files to examine the impact of these policies on birth weight. While the main outcomes of interest are very low birth weight (less than 1,500 grams), low birth weight (less than 2,500 grams), and average birth weight, I also examine the effect of PDMPs and mandatory use policy on other infant health outcomes including preterm births and admission to neonatal intensive care unit.

My results suggest that both PDMP and mandatory use of PDMPs have, at best, a very small

^{1.} Most states allow prescribers to choose other employees to access the PDMPs on prescriber's behalf.

impact on infant health. For instance, the estimated effect of PDMP and mandatory use policy on very low birth weight is 0.54 percent and 0.36 percent respectively. In the preferred specification, none of these estimates are statistically different from zero. I also do not find that these policies affect other infant health outcomes such as preterm births and admissions to neonatal intensive care units. Mandatory use policy, however, increases infants that experience seizures at birth. I explore possible mechanisms underlying these infant health results by examining impact on treatment admissions for opioid misuse, incidence of neonatal abstinence syndrome, and hospital use for opioid use. My results suggest that part of the mechanism underlying these results is substitution from prescription opioids to heroin as indicated by an increase in treatment admissions for heroin misuse after policy adoption.

This paper contributes to a growing literature that examines the effect of policies to reduce opioid misuse by examining the effect of PDMP and mandatory use of PDMPs on opioid misuse among reproductive age women and on infant health outcomes. It has important policy implications as policymakers look for ways to reduce opioid use during pregnancy and NAS incidence (Protecting Our Infants Act of 2015) ². Moreover, as a large number of states are investing in PDMPs, and health care costs associated with opioid crisis (Patrick et al. 2012) are rising, it is important to evaluate the effect of these policies on infant health.

2 CONTEXT

2.1 Opioid use in pregnancy and infant health

I begin this section by discussing the expected effect of opioids on infant health to provide context for why PDMPs might affect birth weight, and other infant health outcomes. Opioids alleviate pain by binding to opioid receptors in the brain. While effective when used as prescribed, their ability to boost pleasure makes them addictive. When taken in large quantities, opioids can reduce breathing and heart rate, and possibly lead to death. Although, illegal opioids like heroin and fentanyl are responsible for more deaths in recent years, prescription opioids like Oxycontin

^{2.} This act required the Department of Health and Human Services to develop recommendations for preventing and treating prenatal opioid exposure, and its associated effects on infants. S.799-114th Congress (2015-2016).

are considered the main drivers of the current crisis. Prescription opioids gained prevalence in the late 1990s after the introduction of Oxycontin and increased emphasis on treating pain with drugs. Between 1999 and 2014, the sales of prescription opioids nearly quadrupled. For instance, in 2012 the prescribing rate reached its peak at 81.3 opioid prescriptions per 100 persons (CDC 2017). Corresponding to an increase in opioid prescriptions, opioid misuse among reproductive age women has increased. For instance, between 1999 and 2014 the opioid use disorder rates at delivery more than quadrupled (Haight et al. 2018). Figure 1 shows a steady increase in treatment admissions for prescription-opioid misuse among reproductive age women between 2000 and 2011, and a dramatic increase in heroin-related treatment admissions after 2011 ³.

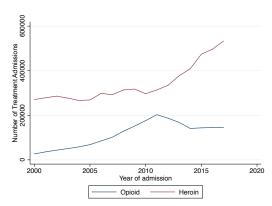


Figure 1: Trends in Treatment Admissions for Opioid and Heroin Misuse

Notes: This figure shows the number of treatment admissions for opioid and heroin misuse for reproductive age women between the ages 15-44. This figure uses TED-A data for 2000-2017.

Opioid use during pregnancy can affect birth outcomes in several ways. The most commonly mentioned consequence is neonatal abstinence syndrome (NAS)- a drug withdrawal syndrome experienced by infants exposed to opioids in utero. Infants born with NAS experience symptoms like irritability, poor sucking reflex, impaired weight gain, respiratory difficulties, and seizures (Patrick et al. 2012). Corresponding to increased opioid consumption during pregnancy, the NAS incidence has also increased. For instance, NAS incidence increased by 300 percent, from 1.5 to 6 per 1000 births, between 1999 and 2013 (Ko et al. 2016). Medical literature suggests that infants with NAS are more likely to be low birth weight (less than 2,500 grams) and preterm (less than 37 weeks gestation). In addition, they are more likely to be admitted to neonatal intensive

^{3.} One explanation for these changes in 2010/2011 is the introduction of abuse deterrent formulation of Oxycontin in 2010 (Alpert, Powell, and Pacula 2018; Evans, Lieber, and Power 2018).

care units. Not surprisingly, this has contributed to increased health care costs. For instance, in 2012 the estimated hospital costs for NAS infants was around \$66,700 compared to \$3,500 for uncomplicated births (Patrick et al. 2015). Maternal opioid use is additionally linked to increased probability of labor and delivery complications like preeclampsia, premature labor and membrane ruptures (Whiteman et al. 2014). Limited evidence suggests that the effects of in utero opioid exposure may continue in early years of childhood (Ross et al. 2015).

The medical literature also suggests that opioid exposure before birth is associated with low birth weight (less than 2,500 grams) and preterm births (less than 37 weeks gestation). For example, A. Fill et al. (2018) use Tennessee Medicaid and birth certificate data to document that children with NAS are significantly more likely to be low birth weight (24 percent versus 9.2 percent), and more likely to be preterm (21.6 percent versus 11.1 percent) compared to children without NAS. Lind et al. (2015) and Hunt et al. (2008) find similar results. In addition, medical literature suggests that infants of pregnant women that receive medications for opioid use disorder like methadone and buprenorphine are at a lower risk of NAS, have less severe NAS, require shorter treatment time, and have higher gestational age and birth weight compared to infants of untreated women (Brogly et al. 2014). Although the above literature suggests that opioid misuse is associated with poor birth weight outcomes, it is likely that factors that contribute to substance use disorder also affect infant health. For example, mothers living in poverty are more likely to misuse opioids (Smith and Lipari 2017). These mothers are also likely to give birth to infants with poor health (Almond, Hoynes, and Schanzenbach 2011). Moreover, mothers who misuse opioids might also be using other substances like cigarette smoking and alcohol that could adversely affect birth outcomes (Romberg et al. 2019).

This discussion implies that policies that reduce prescription opioid misuse during pregnancy may improve infant health. If these policies, however, lead individuals to shift to illegal drug use the infant health outcomes might not change or become worse. In this paper, I focus on the following measures of infant health: fraction of infants with very low birth weight (less than 1,500 grams), fraction of infants with low birth weight (less than 2,500 grams), and average birth weight. While I examine the effect of PDMP and mandatory use of PDMPs on NAS incidence,

that is not the main focus of the paper for the following reasons. First, birth weight is considered a standard measure of infant health and is known to affect adult outcomes (Almond, Currie, and Duque 2017; Prinz et al. 2018). In contrast, NAS has not been linked to adult outcomes yet. Second, NAS numbers are not comparable across states as diagnostic procedures differ by states so I focus on objective measures associated with NAS diagnosis (McQueen and Murphy-Oikonen 2016). Thirdly, an increased awareness about opioid misuse could potentially lead to a reporting bias. Finally, data on NAS have limited availability for the analysis period ⁴.

In a paper written concurrently with this paper, Gihleb et al. (2020) study the impact of PDMPs on NAS. Using State Inpatient Databases for 28 states that have these data available for 2003-2013, the authors find that operational PDMPs reduce the incidence of NAS by 10 percent and have a small or no significant impact on birth outcomes. Their results suggest that mandatory use of PDMPs further reduced NAS incidence, however, these estimates are imprecise as several states adopted mandatory use policy after 2012 and NAS incidence data is not available for many of these states. My work builds on this paper in several ways. First, I extend the study period through 2018, a period when many states adopted the mandatory use of PDMPs. Only 6 states had a mandatory use policy by 2013, but 33 states had adopted the policy by the end of 2018. This period is also important as the opioid crisis has evolved over time with illegal drugs like heroin driving the current crisis compared to prescription opioids in the period analyzed by Gihleb et al. (2020). Second, I use several data sources including Treatment Admissions Data Set (TEDS-A), inpatient hospital admissions, and emergency department use data to understand the mechanisms underlying the infant health results.

2.2 Prescription Drug Monitoring Programs (PDMPs)

Several federal and state policies have been adopted to reduce prescription opioid misuse. A consistent hurdle in the success of these policies, however, is the availability of close substitutes like heroin. For example, abuse deterrent formulation of Oxycontin, a commonly abused

^{4.} State Inpatient Database of the Health care Cost and Utilization Project are not publicly available for all the states, the Kids' Inpatient Database does not include state identifiers after year 2012, and the National Inpatient Sample(NIS) does not contain state identifiers.

prescription drug, failed to reduce opioid-related mortality as prescription opioid users shifted to heroin (Alpert, Powell, and Pacula 2017; Evans, Lieber, and Power 2018). Meara et al. (2016) also find that state policies like limits on day supply, patient identification requirement, pain clinic regulations, use of tamper-resistant prescription pads, and physician examination requirement did not affect opioid misuse in the disabled Medicare population. Meinhofer (2016), however, finds that pain clinic crackdown in Florida was successful in reducing opioid-related hospitalizations and deaths.

Another state-level policy to reduce prescription opioid misuse is the prescription drug monitoring programs (PDMPs). PDMPs were first introduced in New York in 1918 to track prescriptions for heroin and cocaine (TTAC 2018). The earlier databases were paper based, developed for law enforcement agencies, and provided limited or no access to medical providers. In recent years, states have introduced electronic databases that track patient's prescription histories for controlled substances. Giving medical providers access to patient's prescription histories can help them in detecting drug misuse, identify dangerous drug combinations (such as opioids and benzodiazepines), and recommend substance abuse treatment. At the same time, the PDMPs have been criticized for disrupting clinical work flow, compromising patient privacy, and affecting the quality of care for patients that need opioids for medical reasons (Haffajee, Jena, and Weiner 2015). These databases are additionally criticized for contributing to rising illegal opioid use (Beletsky 2015).

Despite the criticisms, many states have adopted the PDMPs. By the end of 2018, 49 states had an operational PDMP and 33 states required prescribers to access the PDMPs before prescribing. Although, widely adopted, the database features vary across states. Most databases collect patient, prescriber, and dispenser's names and contact information, pharmacy name and license number, and the name, dosage and number of days supply for the drugs. The databases differ, however, in frequency of data collection, issuing unsolicited reports, controlled substances monitored, and mandatory registration requirements⁵. Prior research on non-mandatory use databases finds mixed results. While Meara et al. (2016); Paulozzi, Kilbourne, and Desai (2011) and Meinhofer (2017) find no impact on opioid misuse, Radakrishnan (2014), Bao et al. (2016), and Mallat

^{5.} See Bao et al. (2016) for a review of state prescription monitoring databases.

(2017) find that these databases reduce opioid misuse. A possible explanation for the differences in results is different measures of opioid misuse ⁶.

To increase PDMP use, many states now mandate that prescribers access these PDMPs before prescribing under certain circumstances (the mandatory use policy). Evidence suggests that the mandatory use policies are successful in increasing PDMP use. For instance, the requests for patient history reports increased from 11,000 per month to about 1.2 million requests after the mandatory use policy was adopted in New York (The Pew Trust 2016). The mandatory use policy also varies across states. For example, through the end of 2014 the mandatory use policy in Kentucky applied to all prescribers, but Washington's policy only applied to worker's compensation specialists and opioid treatment programs (*Prescription Monitoring Program State Profiles-Washington* 2014). This distinction is important as PDMPs should have a greater impact on opioid misuse if more prescribers are required to consult them. Additionally, some early adopters like Nevada and Delaware only required prescribers to use the databases if drug misuse was suspected. In recent years, states have adopted more comprehensive policies that apply to all prescribers and a wide range of controlled substances.

Several studies have examined the effects of mandatory use of PDMPs on opioid misuse. Buchmueller and Carey (2018) use a difference-in-differences framework to find that prescription drug misuse in Medicare Part D declined significantly in mandatory use states. Meinhofer (2017) also finds that mandatory use policy is associated with a decline in opioids sold and prescription opioid-related deaths. Using National Survey of Drug Use and Health (NSDUH), Ali et al. (2017) find that self-reported opioid misuse declined in mandatory use states. Meinhofer (2017) and Mallat (2017), however, also find some evidence of substitution from prescription opioids to heroin in mandatory use states. Grecu et al. (2019) examine substance use treatment admissions related to prescription drugs as a measure of drug misuse. They find that prescription drug abuse declined in mandatory use states and the effect is strongest among young adults (ages 18-24) ⁷. These stud-

^{6.} For instance, Paulozzi, Kilbourne, and Desai (2011) study the effect of PDMPs on opioid overdose mortality, and opioid consumption by state while Mallat (2017) focuses on oxycodone shipments etc.

^{7.} A recent working paper finds that after Kentucky adopted the mandatory use policy, compared to a control state (Indiana), forty percent of low-volume opioid prescribers stopped prescribing opioids, and among other providers, providers prescribed opioids to approximately sixteen percent fewer patients (Buchmueller, Carey, and Meille (2019).

ies, however, differ in their classification of mandatory use states. While Buchmueller and Carey (2018), Meinhofer (2017) and Mallat (2017) focus on states that mandated database use by all prescribers, Ali et al. (2017) and Grecu et al. (2019) also include states where the mandatory use policy applied only to worker compensation specialists, pain management clinics, and opioid treatment programs. Some recent work also explores the effect of PDMP on other societal outcomes. For example, Gihleb et al. (2019) find that while operational PDMPs had no effect, mandatory use of PDMPs reduced foster care admissions by 10 percent. Similarly, Dave et al. (2020) find that PDMPs reduced overall crime by 5 percent.

3 DATA

Birth Outcomes Data.—To estimate the effect of prescription drug monitoring programs and mandatory use policy on infant health outcomes, I rely on the restricted-use Vital Statistics Natality files for years 2003-2018. These data are an annual census of birth certificates in the United States and include information on birth weight, gestational age, mother's demographic information, and other infant health outcomes. I restrict the sample to mothers between the ages 15-44 who have a singleton birth and are not missing birth weight data. I collapse the data into cells defined by state and quarter-year. For each cell I calculate the percentage of births below a given birth weight.

Policy Dates.—The treatment variables of interest are the times at which each state adopted these policies. I use dates from Horwitz et al.(2018) to identify times at which states gave prescribers access to modern databases. I hand collected dates for mandatory use policies, and Table A1 in the appendix shows these dates. I collected the dates from several sources including Prescription Drug Abuse Policy System (PDAPS), National Alliances for Model States (NAMDSL) and Brandeis University's PDMP Training and Technical Assistance Center (TTAC). I also compared the dates to prior literature (Buchmueller and Carey 2018; Meinhofer 2014; Mallat 2017; Bao et al. 2017). When the dates did not match, I contacted the state administrators to verify the dates. In this paper, I focus on the states in which mandatory use policy applies to all prescribers of controlled substances as these policies target a larger population of prescribers and are more likely to affect drug misuse that these PDMPs intend to reduce.

As discussed in Section 2.1, the mandatory use requirement varies across states. In this paper, I focus on states that require all prescribers of controlled substances to access PDMPs under certain circumstances. For example, in 2012, a few medical licensing boards in New Mexico introduced mandatory use requirements for specific prescribers, but these requirements were not applicable to all prescribers. Although, my results are robust to using 2012 instead of 2017 as the New Mexico policy date, for the main analysis New Mexico is classified as a non-mandatory state before 2017. Similarly, all states with less comprehensive policies are classified as non-mandatory states for the main analysis.

Other Policy Controls.—For my empirical analysis, I want to isolate the effect of PDMPs and mandatory use policy from other state policies that might impact opioid misuse, and were adopted at the same time. I control for pain clinic regulations that introduced specific requirements regarding pain clinic ownership and registration of pain clinics. A few states adopted these regulations close to the adoption of mandatory use policies (Buchmueller and Carey 2018) and these regulations have been shown to reduce opioid misuse and related deaths in Florida (Meinhofer 2016). These data primarily come from PDAPS ⁸. The other type of laws that might affect opioid misuse are Medical Marijuana Laws (MMLs). Bradford and Bradford (2016) find that prescriptions for pain medications declined in states that legalized marijuana for medical use (MML). Powell, Pacula, and Jacobson (2018) further find that opioid overdose deaths declined more in states that allowed marijuana sales through dispensaries. Therefore, I control for MMLs and dispensaries in my analysis. Finally, I control for naloxone laws that have broadened access to Narcan, a drug that can temporarily reverse an overdose. While, Rees et al. (2017) find that these laws reduced opioid -related deaths, Doleac and Mukherjee (2018) find that naloxone expansion is associated with opioid-related emergency room visits and theft ⁹.

^{8.} http://pdaps.org/datasets/pain-management-clinic-laws.

^{9.} I do not control for specific features of databases such as frequency of data update, permission to have delegate, no prescriber immunity, mandatory registration requirement etc. While Haffajee et al. (2018) show that databases with more features are more effective in reducing opioid misuse, these other features are more likely to affect opioid misuse if prescribers use the prescription databases.

4 EMPIRICAL METHODOLOGY

4.1 Difference-in-Differences

I estimate the effect of PDMP and mandatory use policy using a difference-in-differences framework - comparing differences in outcomes across states before and after policy adoption. Specifically, I estimate the following reduced-form equation:

(1)
$$Y_{st} = \delta_s + \gamma_t + \beta_1(PDMP_{st}) + \beta_2(Mandate_{st}) + X_{st} + \epsilon_{st}$$

where Y_{st} is a measure of infant health outcome for state s at time t. The variables $PDMP_{st}$ and $Mandate_{st}$ are equal to 1 if the state had these policies in place for the entire quarter in which a child begins the third trimester, and zero otherwise 10 . I focus on the third trimester as prior literature suggests that the third trimester is more important for birth weight (Hoynes, Miller, and Simon 2015).

I include state fixed effects, δ_s , to control for unobserved differences between states that are stable over time (such as cost of living) and time fixed effects, γ_t , to control for unobserved differences that are common to all states but vary over time (such as federal policies). I additionally control for state-level policies that might be adopted at the same time as PDMP and mandatory use policies: pain clinic regulations, naloxone laws, medical marijuana laws, and presence of legally protected dispensaries (Meinhofer 2016; Doleac and Mukherjee 2018; Powell, Pacula, and Jacobson 2018). In all specifications, I cluster the standard errors at the state-level to account for correlation within states and weight regression estimates by the number of births in each state-time cell.

The main coefficients of interest are β_1 and β_2 , the difference-in-differences estimates for the effect of PDMP and mandatory use policy. These are identified by comparing outcomes in adopting states to outcomes in non-adopting states before and after policy adoption. My preferred

^{10.} As most states adopted the mandatory use policy towards the end of the year, I divide the data into quarters, assigning policies to a quarter if they were in effect for the entire quarter. That is, I code a state that adopted the policy in November of a given year as having adopted the policy in the first quarter of the next year. Only states with comprehensive mandatory use policies are coded as 1, and states with less comprehensive mandatory use policies are coded as 0.

specification also includes state-specific linear trends. Prior literature suggests that accounting for trends in important as opioid misuse intensity varies across states (Grecu et al. 2019; Pohl 2018).

4.2 Event Study Methodology

The underlying assumption in difference-in-differences framework is that without these policies the outcomes in treatment states would have evolved similarly to control states. I probe the validity of this assumption by doing an event study for each policy using the following equation:

(2)
$$Y_{st} = \delta_s + \gamma_t + X_{st} + \sum_{r=-7,\dots,6} \beta_r Policy_{sr} + \omega_s t + \epsilon_{st},$$

where the dependent variable is outcomes in state s at time t. r is negative in periods before the policy was adopted (leads), and positive in periods after the policy was adopted (lags). r = 0 in the first adoption period. The coefficients, β_r , for negative values of r should be zero if the linear state-specific trends are adequate, and there are no anticipatory effects. All regressions include state and time fixed effects, state-specific linear trends, and state-level policy controls. The estimates are weighted by the number of observations in the relevant state-time cell and standard errors are clustered at the state level.

5 RESULTS

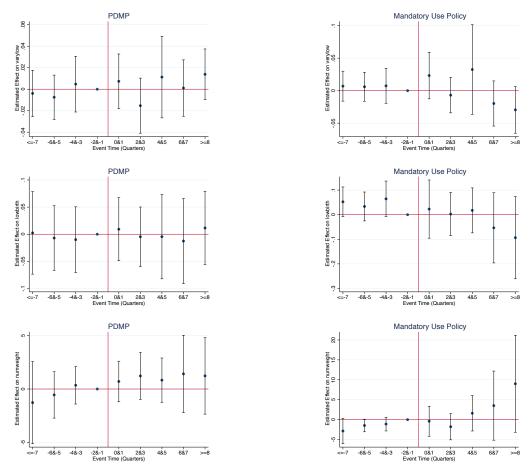
5.1 Impact of PDMP and Mandatory Use Policy on Birth Weight

I begin by presenting event study results for the effect of PDMP and mandatory use policy on birth weight outcomes in Figure 2 ¹¹. The left column shows the point estimates and 95 percent confidence intervals for the effect of PDMP on birth weight outcomes. The right column shows the same for the effect of mandatory use policy. I aggregate event time into six-month bins as aggregate event times makes the coefficient pattern smoother. For both PDMP and mandatory use policy, the figure suggests that pre-policy effects are nearly flat.

I next present the difference-in-differences estimates for the effect of PDMP and mandatory use policy on birth weight outcomes in Table 1. The first column shows estimates with state and

^{11.} Event study graphs without state-specific linear trends are shown in the Appendix.

Figure 2: Event Study for Percentage of Very Low, Low Birth, and Average Birth Weight



Notes: Each figure shows estimates from an event study analysis. The specification includes state fixed effects, time fixed effects, state-specific linear trends, and policy controls. All regressions are weighted by the number of observations in a state-time cell.

time fixed effects. These estimates suggest that PDMP adoption increases the fraction of infants that have very low birth weight, whereas mandatory use policy has no significant effect on very low birth weight births. The estimated effect on low birth weight and average birth weight, however, suggests that mandatory use policy improves birth outcomes by reducing the incidence of low birth weight births and increasing average birth weight. I next include state-specific linear trends in column 2 as the prior literature suggests that accounting for trends is important due to variation in opioid misuse across states (Grecu et al. 2019; Pohl 2018). These estimates are much smaller than the estimates in column 1, and are insignificant. I then include policy controls for MML, MML with dispensary, pain clinic laws, and naloxone laws in column 3. Adding these policy controls makes little difference to my estimates. These estimates suggest that PDMP and mandatory use

of PDMPs has no significant impact on very low birth weight births, low birth weight births, and average birth weight. Moreover, the estimates are small. For example, these estimates suggest that mandatory use policy, at most, increases very low birth weight births by 0.357 percent.

To further understand the effect of these policies on the distribution of birth weight, I follow Hoynes, Miller, and Simon (2015) to estimate difference-in-differences models for the fraction of births that are below a certain number of grams: 1500 grams, 2000 grams, 2500 grams, 3000 grams, and 4000 grams. To get the results in Table 2, I divide the estimated effect by the mean of birth weight outcomes. Similar to Table 1, these estimates also suggest that PDMP and mandatory use policy have, at best, a very small impact on birth weight outcomes.

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Mandate -0.131*** -0.038 (0.044) (0.037) (0.035) Mean of the outcome 6.43 Panel C: Effect of average birth weight (in gms) 0.425 (1.762 1.636 (1.811) (1.430) (1.297) Mandate 7.562** 2.363 1.941 (3.207) (1.934) (1.575) Mean of the outcome 3302.31 State and time fixed effect x x x State-specific linear trends x x x		-0.006	0.001	0.003	
Mean of the outcome (0.044) 6.43 (0.037) (0.035) Panel C: Effect of average birth weight (in gms) (0.044) (0.037) (0.037) (0.035) PDMP 0.425 (1.811) (1.430) (1.430) (1.297) (1.811) (3.207) (1.934) (1.575) Mean of the outcome State and time fixed effect State-specific linear trends (0.037) (0.035) (1.636) (1.297) (1.297) (1.575)		(0.031)	(0.027)	(0.025)	
Mean of the outcome 6.43 Panel C: Effect of average birth weight (in gms) PDMP 0.425 1.762 1.636 (1.811) (1.430) (1.297) Mandate $7.562**$ 2.363 1.941 (3.207) (1.934) (1.575) Mean of the outcome 3302.31 State and time fixed effect x x x State-specific linear trends x x x	Mandate	-0.131***	-0.038	-0.035	
Panel C: Effect of average birth weight (in gms) PDMP 0.425 1.762 1.636 (1.811) (1.430) (1.297) Mandate 7.562** 2.363 1.941 (3.207) (1.934) (1.575) Mean of the outcome 3302.31 State and time fixed effect x x x State-specific linear trends x x x		(0.044)	(0.037)	(0.035)	
PDMP 0.425 1.762 1.636 (1.811) (1.430) (1.297) Mandate 7.562** 2.363 1.941 (3.207) (1.934) (1.575) Mean of the outcome 3302.31 State and time fixed effect x x x State-specific linear trends x x x	Mean of the outcome	6.43			
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	Panel C: Effect of average birth weight (in gms)				
Mandate $7.562**$ 2.363 1.941 (3.207) (1.934) (1.575) Mean of the outcome 3302.31 State and time fixed effect x x x State-specific linear trends x x x	PDMP	0.425	1.762	1.636	
Mean of the outcome (3.207) (1.934) (1.575) State and time fixed effect x x x State-specific linear trends x x x		(1.811)	(1.430)	(1.297)	
Mean of the outcome3302.31State and time fixed effectxxState-specific linear trendsxx	Mandate	7.562**	2.363	1.941	
State and time fixed effect x x x x State-specific linear trends x x x		(3.207)	(1.934)	(1.575)	
State-specific linear trends x x	Mean of the outcome	3302.31			
-	State and time fixed effect	X	X	X	
Policy Controls x	State-specific linear trends		X	X	
	Policy Controls			X	

Note: This table presents the difference-in-differences estimates for the effect of PDMP and mandatory use policy on the percentage of very low birth weight births (less than 1,500 gms), low birth weight births (less than 2,500 gms), and average birth weight. The dependent variable is an indicator for very low and low birth weight multiplied by 100 for ease of interpretation, and average birth weight is in grams. PDMP is an indicator for when prescribers got access to the PDMP electronic database, and mandatory use policy is an indicator for when prescribers were required to access the database. Vital statistics data is collapsed into cells based on state-quarter group. Policy controls are MML, MML dispensary, naloxone laws, and pain clinic laws. All regressions are weighted by the number of observations in a state-time cell. There are 3,264 observations in each column. Clustered standard errors are shown in parentheses. Robust standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

Table 2: Effect of PDMP and Mandatory use Policy on the Distribution of Birth Weights

Birth Weight (in grams)	Percentage Effect of PDMP	Percentage effect of Mandatory use
1500	0.54	0.36
2000	-0.63	0.94
2500	0.05	-0.54
3000	-0.25	-0.38
3500	-0.22	-0.31
4000	-0.08*	-0.03

Note: This table presents the difference-in-differences estimates for the effect of PDMP and mandatory use policy on the distribution of birth weights. The estimates are from regressions that include state and time fixed effects, state-specific linear trends, and policy controls.*** p<0.01, ** p<0.05, * p<0.1.

Table 3: Effect of PDMP and Mandatory use Policy on Other Infant Health Outcomes

	Needed ventilation	NICU	Seizures	Preterm
PDMP	0.022	0.320	-0.024	-0.007
	(0.330)	(0.385)	(0.019)	(0.056)
Mandate	0.119	-0.058	0.021*	0.107
	(0.244)	(0.281)	(0.012)	(0.069)
Mean of the outcome	2.545	7.297	0.042	10.350
Observations	3,264	3,116	3,116	3,264

Note: This table presents the difference-in-differences estimates for the effect of PDMP and mandatory use policy on infant health outcomes. The dependent variables are an indicator for infants who needed ventilation, who were admitted to neonatal intensive care unit (NICU), experienced seizures at the time of birth, and were born before 37 weeks. Vital statistics data is collapsed into cells based on state-time group. All regressions include fixed effects, state-level demographics and policy controls, and state-specific linear time trends. All regressions are weighted by the numbers of observations in a state-time cell. Standard errors are clustered at the state level (shown in parentheses). Robust standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

5.2 Impact of PDMP and Mandatory Use Policy on Other Infant Health Outcomes

I next examine the effect of PDMP and mandatory use policies on other infant health outcomes that section 2.1 suggests might be correlated with opioid exposure in utero. Unlike birth weight outcomes, these outcomes generally tend to either be more extreme or rare. The estimates in Table 3 suggest that PDMP and mandatory use policy have no significant effect on the number of infants that needed ventilation, admissions to neonatal intensive care units, and preterm births. The estimated effect for mandatory use policy on the number of infants that experienced seizures, however, is positive and significant at the 10 percent level.

6 ROBUSTNESS CHECKS

I next perform a series of robustness checks. My results are generally robust. I first sequentially exclude each state and re-estimate equation 1 to verify that my estimates are not driven by one particular state. Figure A2 shows these estimates. The results are generally similar to the main estimates in Table 1. As all the states adopted mandatory use of PDMPs after the reformulation of OxyContin in 2010, I next drop the 10 states that Alpert et al. (2018) list as states with highest rates of Oxycontin misuse. The states dropped from the analysis in Table A2 include Rhode Island, West Virginia, Utah, Wisconsin, Massachusetts, Kentucky, Montana, Indiana, Nevada, and Alaska. Again, the estimates in Table A2 are similar to the main estimates in Table 1. I then estimate equation 1 controlling for the supply of treatment centers as access to treatment centers can affect opioid use and infant health outcomes. In Panel A of Table A3 I control for the number of treatment centers and in Panel B I control for number of treatments centers that specifically accept pregnant women. I use National Survey of Substance Abuse Treatment Services (N-SSATS) to get the number of treatment centers for each state in the sample period. Results in Table A3 are similar to my main estimates. I finally use two-year lag to estimate difference-in-differences models. As suggested by Grecu et al. (2019) it is likely that the effect of these policies materializes after some lag due to time needed to adjust physician behavior, and affect opioid prescriptions and use. The estimates in Table A4 suggest that the effect is concentrated at the lower end of the distribution (significant at the 10 percent level).

7 MECHANISMS

In this section I discuss some of the mechanisms by which PDMP and mandatory use of PDMPs might affect infant health outcomes. While some of the mechanisms can be tested directly using the available data, most of the following discussion is speculative as my research design and data do not allow me to distinguish between plausible mechanisms. I begin by examining the effect of PDMP and mandatory use policy on opioid misuse among reproductive age women (ages 15-44). While the prior literature has looked at opioid misuse in the general population, for thinking

about infant health outcomes reproductive age women is an important population. I use Treatment Episode Data Set-Admissions (TEDS-A) to measure opioid misuse as probability of treatment admission for opioid misuse. These data are collected by the Substance Abuse and Mental Health Services Administration (SAMHSA), and is a national census of yearly admissions to substance abuse treatment facilities that receive federal funding. Although TEDS has been used by prior work (Grecu et al. 2019; Powell, Pacula, and Jacobson 2018; Radakrishnan 2013), it has some limitations. First, the treatment admissions do not uniquely identify individuals. For example, if a person is admitted to a treatment facility three times, the data would show this as three separate admissions. Second, data are missing for certain states for some years. Third, there is variation in types of data reported by states. For example, some states do not report data from correctional facilities (state prisons and jails) while others do (SAMHSA 2013). Fourth, treatment facilities usually operate at a capacity so the number of treatment admissions may not accurately measure drug misuse (Doleac and Mukherjee 2018). Lastly, this data is particularly tricky for measuring opioid misuse among pregnant women as many treatment facilities do not provide treatment services to pregnant women. Moreover, most programs that treat pregnant women do not offer medications used to treat opioid use disorder. Like other data characteristics, pregnancy status at the time of admissions is also not reported by all the states for all sample years (SAMHSA 2013b). Additionally, it is not clear if a decrease in treatment admissions or an increase in treatment admissions suggests reduced opioid misuse. For example, it is possible that PDMPs and mandatory use policies lead to increase in treatment admissions as physicians are likely to identify opioid misuse after these policies. At the same time, it is also possible that reduced initiation rates lower treatment admissions. Buchmueller, Carey, and Meille (2019) find that providers in Kentucky prescribed fewer opioids compared to providers in Indiana after Kentucky adopted the mandatory use policy. Moreover, treatment admissions for substance misuse is arguably an extreme measure of misuse, and not every woman who reduced opioid use as a result of these policies would show up in the treatment admissions data.

In spite of these limitations, I estimate the effect of PDMP and mandatory use policy on opioid and heroin related treatment admissions to understand the mechanisms underlying the infant

health results. I define policy dates at the year level rather than quarter level as TEDS data only reports the year of admission. Regressions are weighted by the number of treatment admissions in each state-year cell. I present the event study results in Figure A.3 in the Appendix that indicate pre-policy effects are nearly flat. I then present the difference-in-differences estimates in Table 4 for reproductive age women. In the first column, I use primary substance of abuse to measure opioid related admissions, and in the second column I use both primary and secondary substance of abuse (SUB1 and SUB2). The estimates in Panel A suggest that PDMP adoption reduces treatment admissions for opioid misuse. In particular, there is a 10.5 percent reduction in treatment admissions for opioid misuse. Mandatory use policy does not lead to any further reduction in treatment admissions for opioid misuse. The estimates in Panel B, however, suggest that these policies lead to an increase in heroin misuse. In particular, there is a 1.471 percentage point increase in treatment admissions for heroin misuse after PDMP adoption, and a 2.706 percentage point increase after mandatory use policy adoption. This finding is consistent with the prior literature that suggests that PDMP and related policies might lead to substitution from prescription opioids to illegal opioids (Meinhofer 2017; Mallat 2019)¹². I next present the results for the effect of these policies on treatment admissions for pregnant women in Table 5. These results suggest that PDMP reduces treatment admissions for opioid misuse by 2.075 percentage points (13.42 percent decline relative to the mean), while mandatory use policy has no additional effect. While the estimates in Panel B of Table 5 are similar in magnitude to estimates in Table 4, these estimates are not statistically significant.

To further understand the mechanisms underlying the infant health results, I next examine other intermediate outcomes that might be affected by these policies. I begin this analysis by following Gihleb et al. (2020) to examine the effect of PDMP and mandatory use policy on Neonatal Abstinence Syndrome (NAS). As mentioned in Section 2.1, NAS numbers are not comparable across states due to differences in diagnostic procedures so these results should be interpreted with caution. For this analysis I obtain NAS rates per 1,000 newborn hospitalization from Healthcare Cost and Utilization Project (HCUP) for years 2008-2017 ¹³. These estimates are presented in

^{12.} I find similar results when I drop states that are missing data for any year.

^{13.} https://www.hcup-us.ahrq.gov/faststats/NASMap

Table 4: Effect of PDMP and Mandatory use Policy on Treatment Admissions-Reproductive Age Women

	<u> </u>	<u> </u>	1		
	Primary Substance	Primary and Secondary Subs	stance		
	Panel A: Effect on Treatment Admissions for Opioid Misuse				
PDMP	-1.037**	-1.676***			
	(0.516)	(0.602)			
Mandate	-0.851	-0.265			
	(1.015)	(1.310)			
Mean of the outcome	9.86	14.15			
Observations	748	748			
	Panel B: Effect on Treatment Admissions for Heroin Misuse				
PDMP	1.471*	1.237			
	(0.821)	(0.760)			
Mandate	2.706**	2.791**			
	(1.314)	(1.291)			
Mean of the outcome	18.16	20.69			
Observations	748	748			

Note: This table presents the difference-in-differences estimates for the effect of PDMP and mandatory use policy on opioid and heroin misuse among reproductive age women. The dependent variable is an indicator for treatment admissions for opioid and heroin misuse. Treatment admissions data is collapsed into cells based on state-time. All regressions include state and time fixed effects, state-specific linear trends, and policy controls. All regressions are weighted by the number of observations in a state-year cell. Standard errors are clustered at the state level (shown in parentheses). *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 5: Effect of PDMP and Mandatory use Policy on Treatment Admissions-Pregnant Women

	Primary Substance	Primary and Secondary Substance				
Pa	Panel A: Effect on Treatment Admissions for Opioid Misuse					
PDMP	-1.724	-2.075*				
	(1.156)	(1.224)				
Mandate	-0.481	0.443				
	(2.002)	(2.149)				
Mean of the outcome	e 11.18	15.46				
Observations	741	741				
Pa	nel B: Effect on Treatm	ent Admissions for Heroin Misuse				
PDMP	0.096	-0.034				
	(1.013)	(0.975)				
Mandate	2.580	2.652				
	(1.702)	(1.731)				
Mean of the outcome	e 19.13	21.69				
Observations	741	741				

Note: This table presents the difference-in-differences estimates for the effect of PDMP and mandatory use policy on opioid and heroin misuse among pregnant women. The dependent variable is an indicator for treatment admissions for opioid and heroin misuse. Treatment admissions data is collapsed into cells based on state-time. All regressions include state and time fixed effects, state-specific linear trends, and policy controls. All regressions are weighted by the number of observations in a state-year cell. Standard errors are clustered at the state level (shown in parentheses). *** p<0.01, ** p<0.1. p<0.1.

Table 6: Effect of PDMP and Mandatory use Policy on NAS and Hospital Use				
	NAS	Inpatient	ED	
PDMP	-0.01	-0.567	3.852	
	(0.179)	(4.637)	(6.187)	
Mandate	0.411	-2.847	8.60	
	(0.267)	(5.828)	(7.51)	
Mean of the outcome	4.99	217.99	141.81	
Observations	439	599	419	

Note: This table presents the difference-in-differences estimates for the effect of PDMP and mandatory use policy on NAS, inpatient hospitalizations, and emergency department use. NAS is the rate of NAS per 1,000 newborn hospitalizations, inpatient is the rate of opioid-related inpatient stays per 100,000 population, and ED is the rate of opioid related emergency department visits per 100,000 population. All regressions include state and time fixed effects, state-specific linear trends, and policy controls. All regressions are weighted by the number of births in a state-year cell. Standard errors are clustered at the state level .*** p < 0.01, ** p < 0.05, * p < 0.1.

column 1 of Table 6. Both the estimates are insignificant. While my estimate for PDMP has the same sign as Gihleb et al. (2020), it is not statistically significant. There are at least two explanations for the difference in results. First, while Gihleb et al.(2020) study period ends in 2013, I extend the data to 2018. As the opioid epidemic has evolved from a prescription opioid crisis to illegal drug use, it is possible that the impact of these policies have changed over time. Second, the HCUP statistics are available for a larger number of states in the latter period so the composition of states might be leading to different results. I next use HCUP data from 2003 to 2018 on opioid related inpatient and emergency department admissions for females as a proxy for hospital use by reproductive age and pregnant women. The estimates in column 2 and 3 suggest these policies have no significant impact on hospital admissions for opioid use.

8 CONCLUSION

In this paper I use the variation in timing of PDMPs and mandatory use policies across states to examine their effect on opioid misuse among reproductive age women and on infant health. Using vital statistics data for 2003-2018, I find that PDMPs and mandatory use policy have no significant effect on birth weight outcomes. I also do not find that these policies affect other infant health outcomes including preterm births, infants needing ventilation, and admissions to neonatal

intensive care units. Mandatory use policy, however, increases the number of infants experiencing seizures at birth. Overall, my results suggest that PDMP and mandatory use policy have, at best, a very small impact on infant health outcomes. While there are several explanations for these results, one possible explanation is that these policies lead to increased heroin misuse among women as indicated by an increase in treatment admissions for heroin misuse. This is consistent with prior literature that finds that policies to reduce prescription opioid misuse lead to increase in heroin misuse (Alpert, Powell, and Pacula 2017; Evans, Lieber, and Power 2018; Mallat 2019). This paper contributes to a growing literature on the effects of policies that target opioid misuse. In particular, by focusing on infant health outcomes, the paper enhances our understanding of how these policies might affect other societal outcomes. Overall, these results have important policy implications as policymakers decide on policies to reduce opioid misuse among reproductive age women and NAS incidence.

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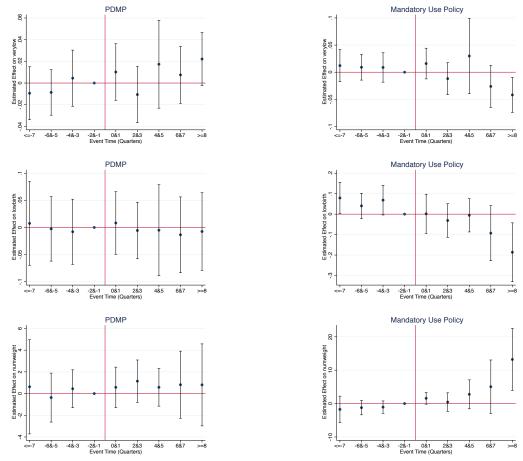
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9 Appendix

9.1 Supplemental Tables for Infant Health Analysis

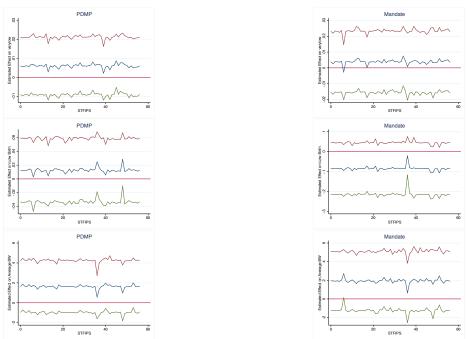
In this section, I present additional figures and tables.

Figure A.1: Event Study for Percentage of Very Low, Low Birth, and Average Birth Weight without state-specific linear trends



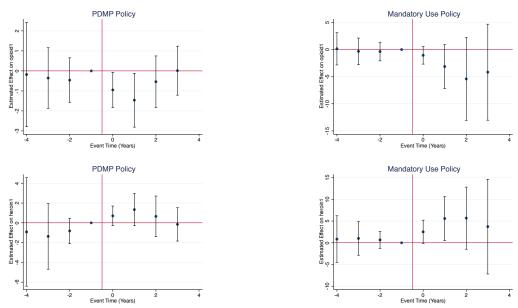
Notes: Each figure shows estimates from an event study analysis. The specification includes state fixed effects, time fixed effects, and policy controls. All regressions are weighted by the number of observations in a state-time cell.

Figure A.2: Robustness Check:Dropping one state at a time



Notes: Each figure shows estimates from sequentially dropping a state. The specification includes state fixed effects, time fixed effects, state-specific linear trends, and policy controls. All regressions are weighted by the number of observations in a state-time cell.

Figure A.3: Event Study for Treatment Admissions-Reproductive Age Women



Notes: Each figure shows estimates from an event study analysis. The specification includes state fixed effects, time fixed effects, and policy controls. All regressions are weighted by the number of observations in a state-year cell.

Table A1: Mandatory Policy Dates			
State	Policy Date		
Alaska	2017Q4		
Arkansas	2017Q4		
California	2018Q4		
Colorado	2018Q3		
Connecticut	2015Q4		
Delaware*	2012Q2		
Florida	2018Q3		
Georgia	2018Q3		
Hawaii	2018Q3		
Illinois	2018Q1		
Kentucky	2012Q3		
Louisiana	2014Q4		
Massachussetss	2016Q2		
Maryland	2018Q3		
Memphis	2017Q1		
Michigan	2018Q2		
Nevada**	2016Q1		
New York	2013Q4		
New Mexico***	2017Q1		
New Jersey	2016Q1		
North Hampshire	2017Q1		
Ohio	2012Q1		
Oklahoma****	2016Q1		
Pennsylvania	2016Q4		
Rhode Island	2016Q3		
South Carolina	2017Q3		
Tennessee	2013Q1		
Texas	2017Q1		
Utah	2016Q4		
Virginia	2015Q3		
Vermont	2014Q1		
Wisconsin	2017Q2		
West Virginia	2012Q3		

Note: This table presents the dates used for mandatory use policy. Dates for PDMP policies are from Horowitz et al. (2018). *Delaware required prescribers to access the PDMP if drug use was suspected starting 2012. **Nevada required prescribers to access PDMPs if drug use was suspected starting 2007, but the state gave prescribers access to the electronic databases in 2011.*** Several licensing boards in New Mexico required prescribers to consult the PDMP starting 2012, but mandatory policy for all prescribers was adopted as a state policy in 2017. ****Oklahoma's mandatory policy initially applied only to prescribers of methadone, and extended to all opioids in 2015.

Table A2: Effect of PDMP and Mandatory use Policy on Birth Weight- high Oxycontin misuse

	Very Low Birth Weight	Low Birth Weight	Average Birth Weight
PDMP	0.004	-0.003	1.711
	(0.008)	(0.027)	(1.428)
Mandate	0.007	-0.040	2.432
	(0.010)	(0.039)	(1.755)
Observations	2,624	2,624	2,624

Note: This table presents the difference-in-differences estimates for the effect of PDMP and mandatory use policy on the percentage of very low birth weight births (less than 1,500 gms), low birth weight births (less than 2,500 gms), and average birth weight after excluding the 10 states with high Oxycontin misuse. The dependent variable is an indicator for very low and low birth weight multiplied by 100 for ease of interpretation, and average birth weight is in grams.PDMP is an indicator for when prescribers got access to the PDMP electronic database, and mandatory use policy is an indicator for when prescribers were required to access the database. Vital statistics data is collapsed into cells based on state-quarter group. Policy controls are MML, MML dispensary, naloxone laws, and pain clinic laws. All regressions are weighted by the number of observations in a state-time cell. Clustered standard errors are shown in parentheses. Robust standard errors in parentheses.*** p < 0.01, ** p < 0.05, * p < 0.1.

Table A3: Effect of PDMP and Mandatory use Policy on Birth Weight- treatment centers

	Very Low Birth Weight	Low Birth Weight	Average Birth Weight
	Panel A: A	ll treatment centers	
PDMP	0.006	0.004	1.579
	(0.008)	(0.024)	(1.192)
Mandate	0.004	-0.033	1.708
	(0.010)	(0.034)	(1.496)
	Panel B: Treatment cer	nters that treat pregna	nt women
PDMP	0.006	0.002	1.690
	(0.008)	(0.024)	(1.262)
Mandate	0.004	-0.035	1.929
	(0.010)	(0.032)	(1.387)
Observations	3,264	3,264	3,264

Note: Note: This table presents the difference-in-differences estimates for the effect of PDMP and mandatory use policy on the percentage of very low birth weight births (less than 1,500 gms), low birth weight births (less than 2,500 gms), and average birth weight. The dependent variable is an indicator for very low and low birth weight multiplied by 100 for ease of interpretation, and average birth weight is in grams.PDMP is an indicator for when prescribers got access to the PDMP electronic database, and mandatory use policy is an indicator for when prescribers were required to access the database. Vital statistics data is collapsed into cells based on state-quarter group. Policy controls are MML, MML dispensary, naloxone laws, and pain clinic laws. All regressions are weighted by the number of observations in a state-time cell. Clustered standard errors are shown in parentheses. Robust standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

Table A4: Effect of PDMP and Mandatory use Policy on Birth Weight Outcomes-with lag			
	(1)	(2)	(3)
Panel A: Effect of very low birth weight (less than 1,500 gms)			
PDMP	0.017**	0.012*	0.012
	(0.008)	(0.007)	(0.008)
Mandate	-0.043**	-0.033*	-0.034*
	(0.017)	(0.018)	(0.019)
Mean of the outcome	1.12		
Panel B: Effect of low birth weight (less than 2,500 gms)			
PDMP	-0.004	0.009	0.013
	(0.030)	(0.025)	(0.023)
Mandate	-0.195**	-0.088	-0.085
	(0.075)	(0.068)	(0.065)
Mean of the outcome	6.43		
Panel C: Effect of average birth weight (in gms)			
PDMP	0.142	0.676	0.503
	(2.063)	(1.589)	(1.445)
Mandate	13.260**	7.849	7.537
	(5.096)	(5.484)	(4.886)
Mean of the outcome	3302.31		
State and time fixed effect	X	X	X
State-specific linear trends		X	X
Policy Controls			X

Note: This table presents the difference-in-differences estimates for the effect of PDMP and mandatory use policy on the percentage of very low birth weight births (less than 1,500 gms), low birth weight births (less than 2,500 gms), and average birth weight. The dependent variable is an indicator for very low and low birth weight multiplied by 100 for ease of interpretation, and average birth weight is in grams.PDMP is an indicator for when prescribers got access to the PDMP electronic database, and mandatory use policy is an indicator for when prescribers were required to access the database. Vital statistics data is collapsed into cells based on state-quarter group. Policy controls are MML, MML dispensary, naloxone laws, and pain clinic laws. All regressions are weighted by the number of observations in a state-time cell. There are 3,264 observations in each column. Clustered standard errors are shown in parentheses. Robust standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1.