Effects of Controlling Prescription Opioids on Child Welfare

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Abstract

This paper examines the effects of Prescription Drug Monitoring Programs (PDMPs) on child maltreatment. Using administrative data on maltreatment allegations and the staggered rollout of PDMPs across states, I separately estimate the effects of modern PDMPs, which provide real-time access to prescription histories, and mandatory-access PDMPs, which require prescribers to consult the database. I find that modern PDMPs did not yield statistically significant effects on maltreatment allegations. In contrast, mandatory PDMPs led to a 16 percent increase in maltreatment allegations. These findings suggest that prescription opioid control policies can generate adverse downstream spillovers for children.

Keywords: Prescription Drug Monitoring Programs (PDMPs), Opioid Epidemic, Child Maltreatment

JEL Codes: I12, I18, J13, J18

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1 Introduction

The opioid epidemic has profoundly affected American families. Beyond its direct impacts on morbidity and mortality, opioid misuse severely diminishes parenting capacity, increasing the likelihood that children will experience maltreatment (Wells, 2009; Rutherford and Mayes, 2017). This connection is quantitatively concerning. One in four American children in 2023 lived with a parent who has a Substance Use Disorder (SUD) (McCabe, McCabe and Schepis, 2025). Between 2000 and 2019, the fraction of children who entered foster care due to parental drug abuse rose from 15 percent to 34 percent (Meinhofer and Angleró-Díaz, 2019; Children's Bureau, 2020). Despite growing evidence that the opioid epidemic has affected children, little is known about how policies aimed at curtailing the supply of opioids affect child welfare.

This paper examines the effects of controlling prescription opioids on child maltreatment through the implementation of Prescription Drug Monitoring Programs (PDMPs). PDMPs are among the most widely adopted supply-side opioid policies in the United States. Existing studies have examined the impacts of PDMPs based on adult outcomes, including prescription opioid use, overdose mortality, doctor shopping, and crime. However, interventions that affect the supply of opioids may also affect children through their impacts on parents. While restricting access to certain opioids can reduce misuse of targeted drugs, it may also induce dependent users to substitute towards illicit and more severe drugs. Given the strong association between parental substance abuse and child maltreatment, the overall effect of controlling prescription opioids on child welfare is an empirical question.

An important challenge in studying the child welfare consequences of opioid policies is distinguishing changes in suspected maltreatment from changes in subsequent institutional responses. The study most closely related to this paper is Gihleb, Giuntella and Zhang (2022), which documents a decline in foster care admissions following the implementation of mandatory PDMPs. Foster care placements, however, are jointly determined by the prevalence of child maltreatment and the decisions and resource constraints of Child Protective Services (CPS). A decline in foster care admissions therefore need not imply an improvement in underlying child welfare: it may reflect fewer cases of maltreatment, a reduced propensity to remove children from home, or both. This paper instead examines maltreatment allegations, which are observed earlier in the child protection process, before CPS placement decisions are made. I find that mandatory-access PDMPs increase maltreatment allegations, suggesting that stricter prescription opioid controls may worsen child maltreatment risk even though prior work finds a decline in foster care admissions.

To identify the causal effects of PDMPs on child maltreatment, I exploit variation across states in the timing of PDMP adoption. States adopted PDMPs in different years, and the programs varied in the requirements imposed on prescribers. Modern PDMPs provide prescribers with electronic, real-time access to patients' prescription histories but do not require them to consult the database. Mandatory-access PDMPs impose an additional requirement that prescribers check the database before prescribing. I separately estimate the effects of modern and mandatory PDMPs using difference-in-differences estimators that are robust to heterogeneous treatment effects under staggered treatment adoption (Callaway and Sant'Anna, 2021).

Using administrative data from the National Child Abuse and Neglect Data System (NCANDS), I find that modern PDMPs did not produce statistically significant changes in maltreatment allegations. In contrast, mandatory PDMPs led to an increase in maltreatment allegations by 40 per 10,000 children, representing a 16 percent increase from the baseline mean prior to implementation. Heterogeneity analysis by maltreatment type shows that physical abuse increased by 35 percent and neglect increased by 18 percent, whereas the effects on sexual abuse were indistinguishable from zero. These findings suggest that stringent supply restrictions on prescription opioids generated unintended consequences that increased child maltreatment risk.

This paper contributes to the literature on supply-side drug policies by documenting their intergenerational consequences and showing that these consequences depend on the intensity of the intervention. Existing studies have examined the effects of PDMPs and other opioid supply restrictions primarily through adult outcomes, including prescription opioid use, overdose mortality, illicit drug use, and crime (Meinhofer, 2018; Grecu, Dave and Saffer, 2019; Kaestner and Ziedan, 2023; Dobkin and Nicosia, 2009; Dobkin, Nicosia and Weinberg, 2014; Alpert, Powell and Pacula, 2018; Evans, Lieber and Power, 2019). This literature shows that policies restricting access to prescription drugs can reduce misuse of targeted substances while also inducing substitution toward illicit drugs. By separately examining modern PDMPs, which improve access to prescription histories, and mandatory-access PDMPs, which additionally require prescribers to consult the database, this paper shows that the child welfare effects arise under the more stringent form of prescription monitoring. These results demonstrate that policies designed to alter adult substance use can generate adverse spillovers for children.

Furthermore, this paper contributes to the child welfare literature by distinguishing changes in suspected maltreatment from subsequent CPS placement decisions. Much of the existing literature studies the consequences of foster care placement for children (Doyle Jr, 2007, 2008; Bald et al., 2022; Baron and Gross, 2022; Gross and Baron, 2022), while a smaller literature examines the determinants of CPS involvement and institutional decision-making (Brown and De Cao, 2020; Prindle, Hammond and Putnam-Hornstein, 2018). Most closely related, Gihleb, Giuntella and Zhang (2022) finds that mandatory-access PDMPs reduce foster care admissions. This paper instead studies maltreatment allegations, which are observed before CPS placement decisions are made, and finds that mandatory-access PDMPs increase allegations. The contrasting responses of allegations and foster care admissions highlight the importance of separating changes in suspected maltreatment from changes in subsequent institutional responses when evaluating the child welfare effects of public policy.

The rest of the paper proceeds as follows. Section 2 provides background information. Section 3 explains details of the data and presents descriptive statistics. Section 4 outlines the empirical strategy. Section 5 presents the results. Section 6 concludes.

2 Background

This section provides background information to contextualize the empirical results of this paper. Section 2.A explains the opioid epidemic in the U.S. and how states have responded to the crisis by laws and policies. Section 2.B presents details about the PDMPs. Section 2.C demonstrates the association between parental drug abuse and child maltreatment.

2.A Opioid Epidemic and State Responses

The opioid epidemic is among the most severe public health crises in U.S. history with far-reaching consequences. In 1999, 2.9 out of every 100,000 people died from an opioid overdose, a number that dramatically jumped to 32.4 per 100,000 by 2021 (CDC, 2023). This unprecedented rise in opioid overdose deaths has prompted the Centers for Disease Control and Prevention (CDC) to declare the worst drug overdose crisis in U.S. history. Studies have documented that the epidemic has led to a range of socioeconomic consequences, including increased health care costs (White et al., 2005; Leslie et al., 2019), higher unemployment and lower labor force participation rates (Harris et al., 2020), higher crime rates (Sim, 2023), and more suicides (Borgschulte, Corredor-Waldron and Marshall, 2018).

In response, states have adopted a variety of regulatory and enforcement measures aimed at curbing opioid misuse and improving prescribing practices. These efforts include triplicate prescription programs, restrictions on over-the-counter access, pill mill laws, and enforcement actions targeting prescribers and pain management clinics. Among these interventions, Prescription Drug Monitoring Programs (PDMPs) have become a central component of state-level strategies. Designed to track the prescribing and dispensing of controlled substances, PDMPs enable real-time monitoring and provide critical data to prescribers, pharmacists, and regulatory agencies. Their widespread adoption reflects growing consensus around their potential to reduce inappropriate prescribing and identify patterns of misuse.

2.B Prescription Drug Monitoring Programs

PDMPs are state-administered databases that track the prescribing and dispensing of controlled prescription medications. Licensed prescribers and pharmacists can access these systems to review a patient's prescription history before issuing or filling a new prescription. Originally designed to support informed clinical decision-making, PDMPs serve as a tool to detect potentially dangerous patterns of drug use, such as doctor shopping or misuse of high-risk medications. First introduced in California in 1939, PDMPs have evolved significantly over time. Early programs operated with limited technological capacity, relying on infrequent data submissions and physical media such as magnetic tapes or computer disks. In contrast, modern PDMPs are fully electronic, updated more frequently, and often integrated into clinical workflows. Many states now mandate their use, enhancing their accessibility and effectiveness in curbing opioid misuse.

While PDMPs are intended to reduce misuse of prescription opioids, empirical evidence suggests that they can generate unintended consequences. Several studies find that mandatory-access PDMPs reduce excessive prescription opioid use, prescription drug abuse, and doctor shopping behavior (Buchmueller and Carey, 2018; Grecu, Dave and Saffer, 2019). At the same time, other studies document increases in heroin overdose deaths, heroin possession, heroin-related crime, and other indicators of illicit opioid use following PDMP implementation (Kim, 2021; Mallatt, 2022, 2018; Meinhofer, 2018). These findings are consistent with substitution from prescription opioids to illicit opioids among individuals with opioid dependence. Because illicit opioids such as heroin are more potent, unregulated, and frequently associated with criminal activity, this substitution may expose families to greater instability than prescription opioid misuse alone. Consequently, although PDMPs may reduce prescription opioid misuse, their overall effects on child welfare are conceptually ambiguous.

2.C Parental Drug Abuse and Child Maltreatment

Policy interventions that affect the prevalence of drug abuse can have significant implications for child welfare, given the well-documented link between parental substance abuse and child maltreatment. Substance abuse significantly impacts reward processing, stress reactivity, and emotional regulation, which are critical components of parenting. As a result, drug addiction diminishes the salience of infant cues and increases the stress associated with caregiving (Wells, 2009; Rutherford and Mayes, 2017). Moreover, parental substance abuse is associated with behaviors that expose children to high-risk environments. For instance, involvement in criminal activity to obtain illicit drugs directly threatens a child's safety and well-being (Powis et al., 2000).

In 2022, parental drug abuse was identified as a risk factor for 23.8% of child maltreatment victims (Children's Bureau, 2022). Furthermore, one study finds that approximately half of mothers of children referred for maltreatment, even in cases without substance-related allegations, have a history of substance use, with opioids being the most commonly used substance (Font and Goldstein, 2024). These patterns suggest a potential link between state responses to the opioid epidemic and the risk of child maltreatment. However, the impact of PDMPs on child welfare is an empirical question, given the mixed effects of these interventions on patterns of substance use. Whether the intended effect of reducing prescription opioid misuse or the unintended effect of a rise in the use of substitute drugs dominates is an empirical question.

3 Data

This section presents information about the data used for the analysis. Section 3.A explains administrative data on child maltreatment allegations. Section 3.B provides details about the sources for PDMP types and implementation years. Section 3.C presents descriptive statistics.

3.A Child Welfare Data

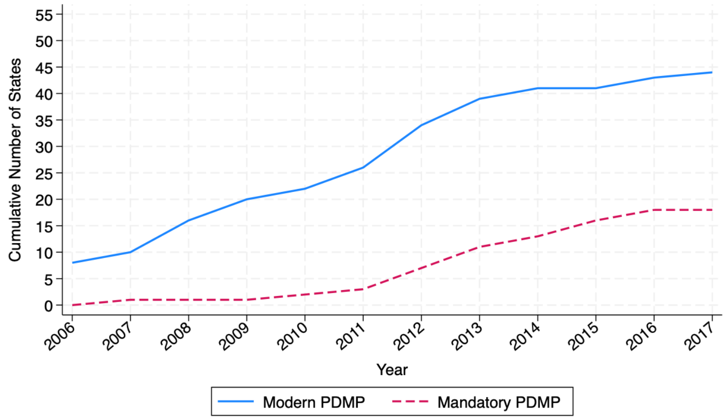
The primary data for the empirical analysis is collected from the National Child Abuse and Neglect Data System (NCANDS). NCANDS is a federally supported program that collects annual data on child abuse and neglect cases reported to CPS nationwide. Although state participation in NCANDS is voluntary, most states, along with the District of Columbia, submitted data during the period covered in this analysis.[1] I use the 2006–2018 NCANDS Child Files to construct outcomes for the 2006–2017 analysis period.[2] Child Files are report-level data that contain detailed information about the reported child and the nature of the allegations.

I focus on allegations reported by professionals because these reports are likely to be less susceptible to changes in reporting behavior and therefore provide a more reliable proxy for changes in maltreatment risk (Evans, Harris and Kessler, 2022; Suh, 2026). Professional reporters include social service, medical, mental health, legal, and education personnel, as well as child care providers. Many of these professionals are mandated reporters and receive training and institutional guidance

[1] Oregon and North Dakota were excluded for not reporting during the sample period.

[2] NCANDS Child Files (CF2006, CF2007, CF2008, CF2009, CF2010, CF2011, CF2012, CF2013, CF2014, CF2015, CF2016, CF2017, CF2018) were used for the analysis. The analysis period of this paper is 2006–2017. I define the year of an allegation based on the year in which the allegation was reported, rather than the year in which the case was submitted to the agency. Because the report year and submission year do not necessarily coincide, I also use the 2018 Child File to minimize the loss of allegations reported in 2017. The datasets were obtained from NDACAN and have been used in accordance with its Terms of Use Agreement License. The Administration on Children, Youth and Families, the Children's Bureau, the original dataset collection personnel or funding source, NDACAN, Duke University, Cornell University, and their agents or employees bear no responsibility for the analyses or interpretations presented here.

Figure 1: Rollout of PDMPs



Notes. This figure reports the cumulative number of states that have implemented PDMPs by each year. North Dakota and Oregon were excluded for not reporting child maltreatment allegations during the sample period.

on identifying and reporting suspected child maltreatment. Throughout the remainder of the paper, I refer to allegations reported by professionals as maltreatment allegations.

One feature of NCANDS Child Files is that county identifiers are masked for counties with fewer than 700 allegations in each year. Excluding masked counties from the empirical analysis would result in censoring bias. To minimize the bias and leverage the regional variation in the outcome variables as much as the data allows, I construct "super counties" in each state following a two-step procedure. First, I identify counties that appear in every year of Child File, i.e., counties with more than 700 allegations each year during the sample period. There are 597 counties that appear in every Child File. These identified counties account for 66 percent of the total population. Second, I construct super counties in each state by aggregating outcome and control variables across all counties with fewer than 700 allegations. This step yields 46 super counties. The final balanced panel consists of 597 identified counties and 46 super counties. For the analysis of modern PDMPs, I excluded counties in 8 states that already adopted PDMPs in 2006 (always-treated counties).

Table 1: Summary Statistics

	(1) Per 10,000 Children	(2) Share of Allegations
Total Allegations	257.50	1
White Children	204.21	0.583
Black Children	436.04	0.260
Female Children	262.08	0.497
Male Children	250.02	0.497
Young Children	233.88	0.433
Old Children	276.48	0.561
Neglect	140.33	0.545
Physical Abuse	62.29	0.242
Sexual Abuse	21.20	0.082

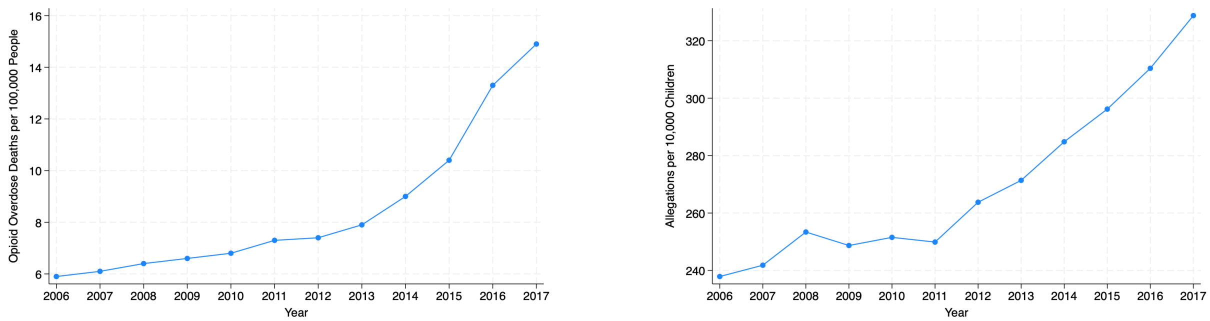
Notes. This table reports summary statistics of the analysis sample based on the National Child Abuse and Neglect Data Systems (NCANDS) Child Files. The sample consists of maltreatment allegations reported between 2006 and 2017. North Dakota and Oregon were excluded from the sample for nonreporting. Young children refer to those younger than the median age of 7, whereas old children refer to those older than 7. Column (1) reports the number of allegations per 10,000 children. Column (2) reports the share of each allegation type relative to the total number of allegations.

3.B PDMP Types and Implementation Years

PDMPs have evolved substantially over time, with considerable variation across states in both their technological features and the requirements imposed on prescribers. To characterize this variation, I distinguish between two features of PDMPs: whether a state operates a modern PDMP and whether it imposes a mandatory-access requirement. The classification of modern PDMPs largely follows Kaestner and Ziedan (2023). Early PDMPs relied on paper-based systems or electronic systems in which prescription data were transferred infrequently or through older technologies such as magnetic tapes or computer disks. Modern PDMPs represent a substantial technological upgrade, providing prescribers with electronic access to up-to-date prescription histories. Mandatory PDMPs impose an additional requirement that prescribers consult the database before prescribing certain controlled substances. The classification and implementation years of mandatory PDMPs follow Gihleb, Giuntella and Zhang (2022).

Figure 1 shows the cumulative number of states adopting each policy feature over time. By 2006, eight states had implemented a modern PDMP, while no state had yet adopted a mandatory-access requirement. Adoption of both features increased throughout the sample period. By 2017, 44 states had implemented a modern PDMP and 18 states had adopted a mandatory-access requirement.

Figure 2: Trends in Opioid Overdose Deaths and Maltreatment Allegations



(a) Opioid Overdose Deaths

(b) Maltreatment Allegations

Notes. This figure plots trends in opioid overdose deaths and maltreatment allegations during the sample period. Figure (a) presents the trends in opioid overdose deaths per 100,000 people. Figure (b) presents the trends in maltreatment allegations per 10,000 children. Figure (a) is based on the data from the National Vital Statistics System. Figure (b) is based on NCANDS Child Files.

3.C Descriptive Statistics

As shown in Table 1, approximately 258 children per 10,000 were investigated by CPS for alleged maltreatment between 2006 and 2017. Black children were disproportionately represented in these investigations, with 436 investigations per 10,000 Black children compared to 204 per 10,000 White children. Neglect was the most common allegation type, accounting for roughly 55 percent of all reports, followed by physical abuse at about 24 percent.

Opioid overdose death rates have risen dramatically since the early 2000s. As shown in Figure 2, opioid overdose deaths per 100,000 people were 5.9 in 2006, but increased substantially over the following decade, reaching 14.9 in 2017. The unprecedented increase in opioid overdoses prompted federal and state governments to adopt policies aimed at curbing the supply of abusable opioids. PDMPs were among the key policies implemented to address the growing misuse of prescription opioids. During this same period, child maltreatment allegations also increased substantially. In 2016, there were 238 maltreatment allegations per 10,000 children. By 2017, this number had risen to 329.

4 Empirical Strategy

This section presents details about the empirical strategy. Section 4.A explains the main empirical estimation framework. Section 4.B assesses the validity of the identifying assumptions.

4.A Estimation Framework

I leverage variation in the timing of PDMP implementation across states to identify the causal effects of PDMPs on child maltreatment allegations. PDMPs were introduced in different years across states, and once implemented, the policy remained in place. These features make this a typical example of a staggered adoption setting. Conventionally, researchers have employed a two-way fixed effects (TWFE) model to estimate the average treatment effect on the treated (ATT). However, a growing body of recent econometric literature has documented that the TWFE model can produce biased estimates in staggered adoption settings with heterogeneous treatment effects and proposed alternative estimators (De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021; Sun and Abraham, 2021; Callaway and Sant'Anna, 2021). The primary concern is that TWFE models compare units that have been treated with those that were treated in earlier periods, leading to "bad comparisons" and potentially generating negative weighting problems, unless treatment effects are homogeneous across treatment cohorts and over time.

To address this identification challenge, I use an estimator developed by Callaway and Sant'Anna (2021) that circumvents bad comparisons and identifies treatment effects in the presence of heterogeneous effects under a staggered adoption design. I use not-yet-treated counties, which belong to states that have not adopted PDMPs up to each period, as the primary control group. The estimator first recovers group-time average treatment effects by comparing counties first treated in year g with an appropriate control group in year t:

$$ATT(g,t) = \mathbb{E}[Y_t(g) - Y_t(0) \mid G = g], \tag{1}$$

where $G = g$ denotes counties first treated in year g, $Y_t(g)$ is the potential outcome under treatment, and $Y_t(0)$ is the untreated potential outcome. I condition on pre-treatment $(g-1)$ county characteristics, including the percentages of female, White, and Black populations, the percentages of six age groups, unemployment and labor force participation rates, and indicators for medical marijuana laws and Medicaid expansion. Standard errors are clustered at the state level to account for within-state correlation in policy adoption and outcomes.

The group-time treatment effects are aggregated into event-study estimates that trace the dynamic effects of PDMP implementation relative to the year immediately preceding adoption:

$$\theta^{event}(e) = \sum_{g \in \mathcal{G}} \mathbf{1}[g + e \leq T] ATT(g, g+e) P(G = g \mid G + e \leq T, C \neq 1), \tag{2}$$

where e denotes event time, $\mathcal{G}$ is the set of treatment cohorts, T is the final year of the sample, and C denotes the control group. These estimands identify the average treatment effect e periods relative to implementation across all eligible treatment cohorts.

In addition to the dynamic effects, I report an average treatment effect over the implementation year and the following four years by aggregating group-time treatment effects over event times 0 through 4:

$$\theta^{simple} = \frac{1}{\kappa} \sum_{g \in \mathcal{G}} \sum_{t=g}^{g+4} ATT(g, t) P(G = g \mid G \leq T), \tag{3}$$

where κ normalizes the weights to sum to one.

4.B Identification and Validity Checks

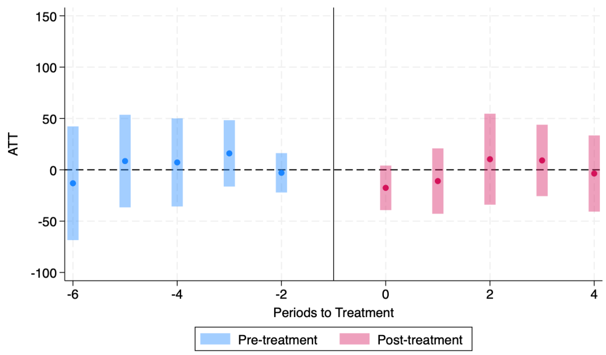
Identification relies on the conditional parallel trends assumption: in the absence of PDMP implementation, treated and control counties with similar observable characteristics would have followed parallel trends in child maltreatment allegations. I assess the plausibility of the identifying assumption in two ways. First, I show that the estimated coefficients on the event-study leads, $\theta^{event}(e)$, are statistically indistinguishable from zero in the pre-PDMP periods. Second, I test whether pre-PDMP county characteristics predict the timing of PDMP implementation. Although the parallel trends assumption is fundamentally untestable, systematic relationships between observable county characteristics and PDMP adoption could raise concerns that treated and control counties followed different underlying trajectories even before treatment.

These observable characteristics include county-level demographic and economic variables as well as Schedule II prescription opioids per capita. The latter is particularly important because of the nationwide reformulation of OxyContin in 2010, which differentially affected counties with higher pre-reformulation opioid prescribing (Evans, Harris and Kessler, 2022). If states with greater baseline opioid exposure systematically adopted PDMPs earlier, the estimated treatment effects could confound the effects of PDMP implementation with differential exposure to the OxyContin reformulation. Examining the relationship between PDMP adoption and pre-treatment Schedule II opioid prescribing therefore provides an additional assessment of the identifying assumptions.

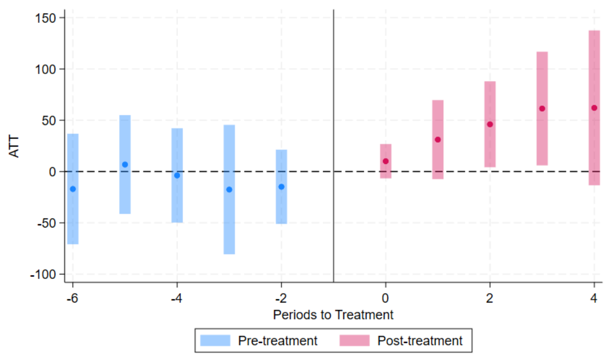
Table A2 presents the relationship between pre-PDMP county-level characteristics and the timing of PDMP implementation. For both modern and mandatory PDMPs, I conduct two sets of comparisons: (1) comparing adopters to never-adopters, and (2) comparing early adopters to late adopters among the adopting counties. Comparison (1) is between counties that adopted PDMPs at any point during the sample period and those that never adopted PDMPs. For Comparison (1), the outcome variable is an indicator that is equal to one if the county's state adopted the corresponding PDMP type at any point during the sample period. For Comparison (2), the outcome variable is the year of the PDMP implementation, with the year 2007 indexed as 1 and subsequent years incrementing by 1.

None of the covariates predict modern PDMP adoption or adoption timing at the 5 percent significance level. For mandatory PDMPs, several covariates including labor force participation, percentage female, and the shares of the population ages 20–24 and 35–44 are statistically significant predictors of adoption relative to never-adopters. When comparing early and late adopting counties, the only significant predictor is the share of Black population. Moving from a county at the 25th percentile (2.3) to 75th percentile (14.5) of the Black population is associated with roughly one year earlier adoption. Because PDMP policies are adopted at the state level whereas racial composition varies substantially within states, this county-level association provides limited evidence of systematic differences in state-level adoption timing. Importantly, baseline Schedule II opioid prescribing is not significantly associated with either PDMP adoption or adoption timing.

Figure 3: Event Study Results for Allegations



(a) Modern PDMP



(b) Mandatory PDMP

Notes. This figure reports point estimates and 95 percent confidence intervals on $\theta^{event}(e)$ from Equation 2. The dependent variable is the number of maltreatment allegations per 10,000 children. Figure (a) presents the results for modern PDMP. Figure (b) presents the results for mandatory PDMP. Standard errors are clustered at the state level.

5 Results

This section presents the empirical results. Section 5.A shows the main results. Section 5.B presents the results by maltreatment types and child characteristics. Section 5.C assesses the robustness of the results.

5.A Main Results

Figure 3 presents the event study results for allegations per 10,000 children following the implementation of modern and mandatory PDMPs. The estimated effects are statistically indistinguishable from zero for every pre-treatment period for both policy types, providing empirical

Table 2: Difference-in-Differences Results for Maltreatment Allegations

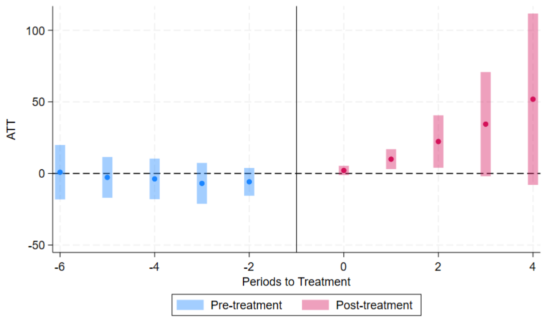
	(1) Modern	(2) Mandatory
ATT	3.68	40.26**
	(14.67)	(17.81)
	[1.5%]	[15.5%]
Mean	250.52	259.23
Observations	6708	7716

Notes. This table reports the point estimates and the standard errors for θ^{simple} from Equation 3. The dependent variable is the number of maltreatment allegations per 10,000 children. Column (1) presents the results for modern PDMP. Column (2) presents the results for mandatory PDMP. Change rates from the pre-PDMP means are reported in the square brackets. Standard errors in parentheses are clustered at the state level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

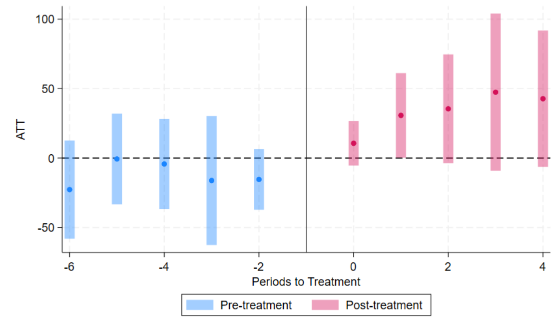
support for the identifying assumption. After implementation, however, the dynamics of the treatment effects diverge. The estimated effects for modern PDMPs remain close to zero and statistically insignificant, whereas the effects for mandatory PDMPs become significant and grow in magnitude over time. Table 2 reports the average treatment effects for the treated counties following the implementation. The estimated coefficient for modern PDMPs is near zero and insignificant, while the coefficient for mandatory PDMPs is approximately 40 allegations per 10,000 children, corresponding to a 15.5 percent rise relative to the pre-PDMP mean.

These estimates capture the reduced-form effect of the policy on suspected maltreatment reported to CPS and do not by themselves identify the underlying mechanism. Nevertheless, the result is consistent with unintended consequences of PDMPs documented in the literature. Mandatory PDMPs can restrict access to prescription opioids, while existing studies find that such restrictions may induce substitution towards illicit opioids and increase heroin-related crime and mortality (Kim, 2021; Mallatt, 2022, 2018; Meinhofer, 2018). Because illicit opioid use may increase household instability, impair parenting capacity, and expose families to criminal activity, substitution toward illicit drugs provides one plausible explanation for the increase in maltreatment allegations.

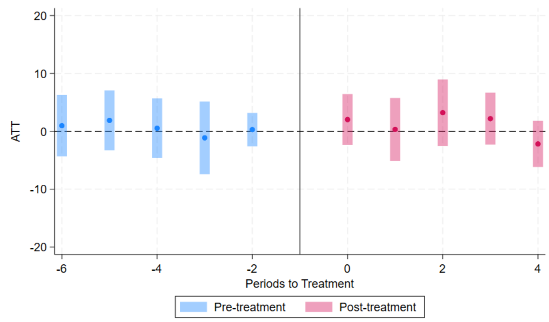
Figure 4: Event Study Results for Mandatory PDMP by Maltreatment Types



(a) Physical Abuse



(b) Neglect



(c) Sexual Abuse

Notes. This figure reports point estimates and 95 percent confidence intervals on $\theta^{event}(e)$ from Equation 2. Dependent variables are the number of physical abuse, neglect, and sexual abuse allegations per 10,000 children. Figure (a) reports the results for physical abuse. Figure (b) reports the results for neglect. Figure (c) reports the results for sexual abuse. Standard errors are clustered at the state level.

5.B Heterogeneity

Figure 4 and Table 3 present the results for the effects of mandatory PDMPs by maltreatment type. Physical abuse and neglect allegations significantly increased following the implementation of mandatory PDMPs. Physical abuse increased by approximately 22 per 10,000 children, corresponding to a 35 percent increase, while neglect increased by 32 per 10,000 children, corresponding to an 18 percent increase. In contrast, the estimated effects for sexual abuse allegations were statistically indistinguishable from zero. Estimated effects for modern PDMPs by maltreatment type are reported in Figure A1 and Table A3, showing that the coefficients are statistically insignificant for all types.

The heterogeneous effects of mandatory PDMPs by maltreatment type are consistent with the

Table 3: Difference-in-Differences Results for Mandatory PDMP by Maltreatment Types

	(1) Physical	(2) Neglect	(3) Sexual
ATT	22.06**	32.33**	1.28
	(9.67)	(15.35)	(1.90)
	[35.4%]	[18.4%]	[5.9%]
Mean	62.38	176.12	21.56
Observations	7716	7716	7716

Notes. This table reports the point estimates and the standard errors for θ^{simple} from Equation 3. Dependent variables are the number of physical abuse, neglect, and sexual abuse allegations per 10,000 children. Column (1) reports the results for physical abuse. Column (2) reports the results for neglect. Column (3) reports the results for sexual abuse. Change rates from the pre-PDMP means are reported in the square brackets. Standard errors in parentheses are clustered at the state level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

distinct etiological causes of sexual abuse. Existing studies have shown that sexual abuse has unique contributing elements that are influenced by the perpetrators' psychological and familial factors, which are distinct from those affecting other forms of child maltreatment (Lee et al., 2023; Younas and Gutman, 2022). While parental substance use is associated with overall rates of child maltreatment, its impact differs across maltreatment types, showing stronger associations with neglect and physical abuse relative to sexual abuse (Lee et al., 2023; Younas and Gutman, 2022).

Figure A3 and Table A5 present the results for the effects of mandatory PDMPs by child characteristics: race, gender, and age. Point estimates are positive across all child subgroups, although the estimate for Black children is imprecisely estimated. The point estimates do not suggest that the effects were concentrated within any particular subgroup. The effects of modern PDMPs by child characteristics are presented in Figure A2 and Table A4, showing that the coefficients are all statistically insignificant across all characteristics.

5.C Robustness Checks

I estimated the treatment effects using the alternative control group, instead of using not-yet-treated counties as the control group. Figure A4 and Table A6 present the event study and difference-in-differences results using never-treated counties as controls. These are the counties that belong to states that did not implement PDMPs during the sample period. The estimates are similar to the main results both in terms of the magnitude and statistical significance.

I also estimated the model using alternative sets of control variables. Figure A5 and Table A7 present specifications that include only economic controls, only demographic controls, or no controls. The economic controls consist of the labor force participation and unemployment rates, while the demographic controls include the shares of the population that are female, White, and Black, along with the shares in six age groups. Across all specifications, the estimated effects of modern PDMPs remain statistically indistinguishable from zero. The estimated effects of mandatory PDMPs remain positive and statistically significant at the 5 percent level when demographic controls are included and at the 10 percent level when only economic controls or no controls are included.

6 Conclusion

The opioid epidemic has imposed substantial health, economic, and social costs on American families. In response, states have increasingly relied on PDMPs as a central policy tool to combat the rising misuse of prescription opioids. The existing literature provides mixed evidence regarding the effectiveness of PDMPs. While several studies document reductions in prescription opioid misuse and doctor-shopping behavior, others highlight unintended consequences, including substitution towards illicit opioids.

This paper examines the downstream consequences of PDMPs for children by studying their effects on child maltreatment allegations. I separately estimate the effects of modern PDMPs, which provide real-time access to prescription histories, and mandatory PDMPs, which require prescribers to consult the database. The estimated effect of modern PDMPs is small and statistically indistinguishable from zero. In contrast, mandatory PDMPs increased maltreatment allegations by approximately 16 percent relative to the pre-implementation mean. The increase was concentrated in allegations of physical abuse and neglect, while the estimated effect on sexual abuse was statistically indistinguishable from zero. These findings complement prior evidence that mandatory PDMPs reduce foster care admissions. Taken together, the contrasting responses of maltreatment allegations and foster care placements highlight the importance of distinguishing changes in suspected maltreatment from changes in subsequent CPS placement decisions when evaluating the child welfare effects of opioid policy.

These estimates capture the reduced-form effect of PDMPs on reported maltreatment allegations and do not directly identify the underlying behavioral mechanism. Nonetheless, the findings are consistent with the possibility that stringent restrictions on the accessibility of prescription opioids can generate adverse spillovers for children. Policies that reduce access to prescription opioids may alter patterns of substance use and increase household instability rather than eliminating the risks associated with parental substance abuse.

The results highlight the importance of considering intergenerational consequences when evaluating opioid control policies. Policies designed primarily to alter prescribing behavior may also affect vulnerable children and increase demands on child-welfare agencies. Complementary investments in substance use treatment, family support, and child protection may therefore be important for reducing unintended consequences while preserving the intended benefits of prescription monitoring.

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Appendix A

Effects of Controlling Prescription Opioids on Child Welfare

Jeongsoo Suh

Table A1: PDMP Implementation Dates

State	Modern PDMP		Mandatory PDMP	
	Month	Year	Month	Year
Alabama	April	2006		
Alaska	January	2012		
Arizona	December	2008		
Arkansas	May	2013		
California	September	2009		
Colorado	February	2008		
Connecticut	July	2008	October	2015
Delaware	August	2012	March	2012
District of Columbia	October	2016		
Florida	October	2011		
Georgia	May	2013		
Hawaii	February	2012		
Idaho	April	2008		
Illinois	December	2009		
Indiana	July	2007	July	2014
Iowa	March	2009		
Kansas	April	2011		
Kentucky	July	1999	July	2012
Louisiana	January	2009	August	2014
Maine	January	2005		
Maryland	December	2013		
Massachusetts	January	2011	June	2013
Michigan	January	2003		
Minnesota	April	2010		
Mississippi	July	2008		
Missouri				
Montana	October	2012		
Nebraska	January	2017		
Nevada	February	2011	October	2007
New Hampshire	October	2014	January	2016
New Jersey	January	2012	November	2015
New Mexico	August	2005	September	2012
New York	June	2013	August	2013
North Carolina	July	2007		
Ohio	October	2006	November	2011
Oklahoma	July	2006	November	2010
Pennsylvania	August	2016		
Rhode Island	September	2012	June	2016
South Carolina	February	2008		
South Dakota	March	2012		
Tennessee	January	2010	January	2013
Texas	August	2012		
Utah	January	2006		
Vermont	November	2013	November	2013
Virginia			July	2015
Washington				
West Virginia	September	2014	June	2012
Wisconsin				
Wyoming				

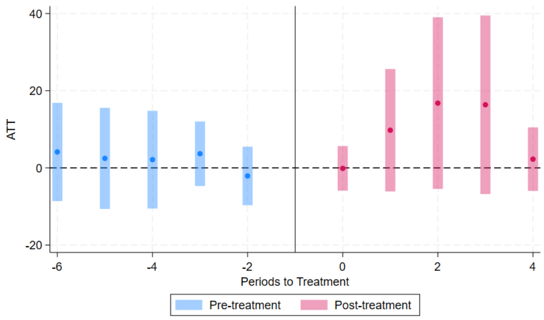
Notes. This table reports the implementation months and years of modern and mandatory PDMPs. Dates for modern PDMP were obtained from Kaestner and Ziedan (2023) and the dates for mandatory PDMP were obtained from Gihleb, Giuntella and Zhang (2022). North Dakota and Oregon were excluded for not reporting child maltreatment allegations.

Table A2: Pre-PDMP County Characteristics and PDMP Implementation Timing

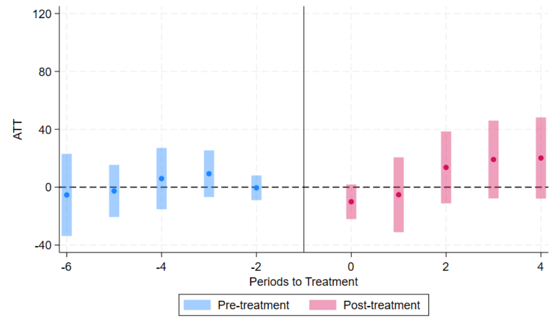
	(1) Mandatory Never vs. Adopt	(2) Mandatory Early vs. Late	(3) Modern Never vs. Adopt	(4) Modern Early vs. Late
Unemployment	-0.02	-0.59*	-0.01	-0.15
	(0.06)	(0.33)	(0.04)	(0.20)
Labor Force Participation	-0.03**	-0.12	-0.01	-0.08
	(0.01)	(0.09)	(0.01)	(0.07)
Percent White	0.01	0.09*	-0.00	0.05
	(0.01)	(0.05)	(0.00)	(0.04)
Percent Black	-0.00	0.10**	-0.00	0.05
	(0.01)	(0.05)	(0.00)	(0.05)
Percent Female	0.17***	0.53	0.01	0.35*
	(0.05)	(0.40)	(0.02)	(0.19)
Percent Age 0 to 19	0.06	-0.42	-0.02	-0.36
	(0.07)	(0.30)	(0.05)	(0.42)
Percent Age 20 to 24	0.16**	0.52	-0.05	0.04
	(0.06)	(0.38)	(0.06)	(0.35)
Percent Age 25 to 34	0.09	-0.69	-0.05	-0.25
	(0.07)	(0.45)	(0.06)	(0.46)
Percent Age 35 to 44	0.25**	1.72*	0.04	-0.01
	(0.12)	(0.87)	(0.09)	(0.82)
Percent Age 45 to 54	0.21*	0.76	-0.12*	1.06
	(0.11)	(0.92)	(0.06)	(0.91)
Percent Age 55 to 64	0.22	-1.05	-0.08	-0.89
	(0.19)	(1.07)	(0.16)	(1.33)
Schedule II Prescription Opioids per Capita	0.13	-0.36	0.01	-1.65
	(0.24)	(0.55)	(0.07)	(1.01)
Constant	-13.22***	-22.40	2.62	-7.04
	(3.41)	(22.87)	(2.51)	(13.93)
Observations	643	227	559	498
R^2	0.18	0.41	0.07	0.12
F	3.64	2.61	0.56	0.92

Notes. This table presents the relationship between county characteristics in 2006 and PDMP implementation timing. Columns (1) and (2) show the results for mandatory PDMPs, whereas Columns (3) and (4) show the results for modern PDMPs. The dependent variable for Columns (1) and (3) is an indicator that is equal to one if the county's state adopted the corresponding PDMP type at any point during the sample period. The dependent variable for Columns (2) and (4) is the year of the PDMP implementation, with the year 2007 indexed as 1 and subsequent years incrementing by 1. Standard errors are clustered at the state level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

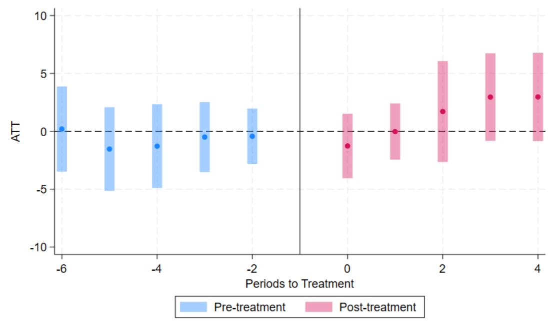
Figure A1: Event Study Results for Modern PDMP by Maltreatment Types



(a) Physical Abuse



(b) Neglect



(c) Sexual Abuse

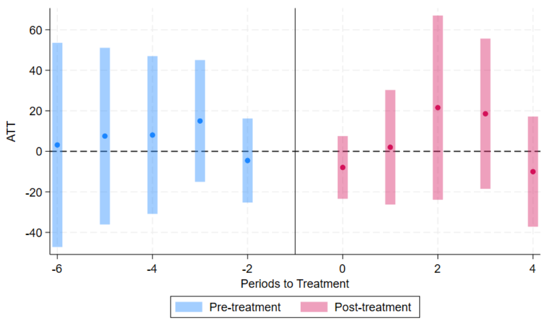
Notes. This figure reports point estimates and 95 percent confidence intervals on $\theta^{event}(e)$ from Equation 2. Dependent variables are the number of physical abuse, neglect, and sexual abuse allegations per 10,000 children. Figure (a) reports the results for physical abuse. Figure (b) reports the results for neglect. Figure (c) reports the results for sexual abuse. Standard errors are clustered at the state level.

Table A3: Difference-in-Differences Results for Modern PDMP by Maltreatment Types

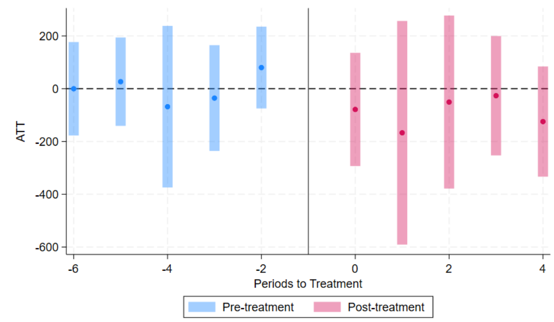
	(1) Physical	(2) Neglect	(3) Sexual
ATT	8.99	7.21	1.23
	(6.45)	(10.47)	(1.36)
	[14.6%]	[5.4%]	[5.7%]
Mean	61.57	133.69	21.69
Observations	6708	6708	6708

Notes. This table reports the point estimates and the standard errors for θ^{simple} from Equation 3. Dependent variables are the number of physical abuse, neglect, and sexual abuse allegations per 10,000 children. Column (1) reports the results for physical abuse. Column (2) reports the results for neglect. Column (3) reports the results for sexual abuse. Change rates from the pre-PDMP means are reported in the square brackets. Standard errors in parentheses are clustered at the state level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

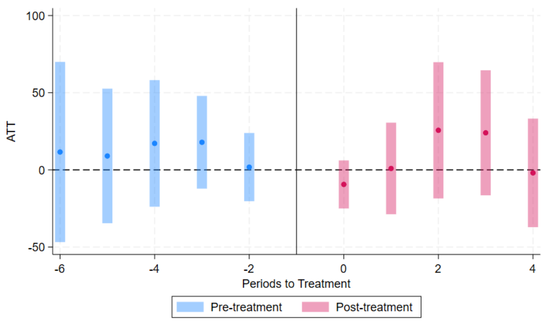
Figure A2: Event Study Results for Modern PDMP by Child Characteristics



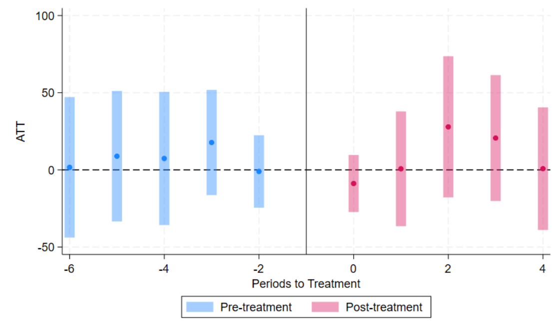
(a) White



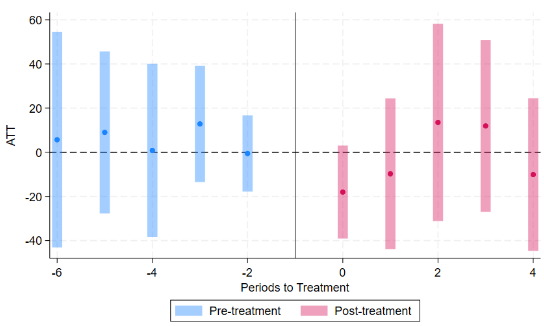
(b) Black



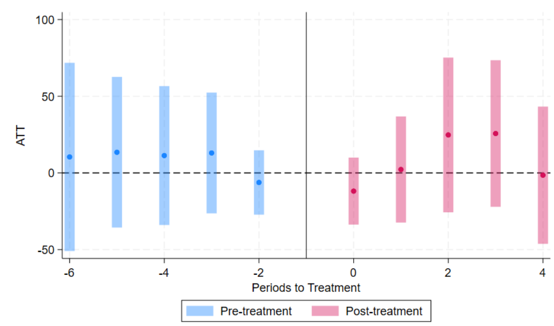
(c) Male



(d) Female



(e) Young



(f) Old

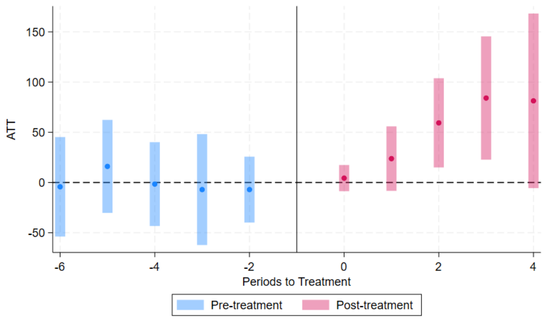
Notes. This figure reports point estimates and 95 percent confidence intervals on $\theta^{event}(e)$ from Equation 2. The dependent variable is the number of maltreatment allegations per 10,000 children by child characteristics: race, gender, and age. Young children refer to those younger than the median age of seven, whereas old children refer to those older than seven. Standard errors are clustered at the state level.

Table A4: Difference-in-Differences Results for Modern PDMP by Child Characteristics

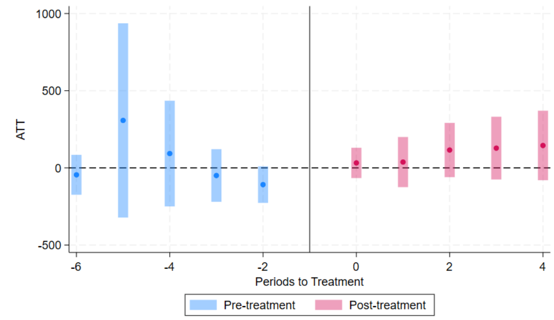
	(1) White	(2) Black	(3) Male	(4) Female	(5) Young	(6) Old
ATT	4.84	-89.47	7.75	8.12	-2.58	7.76
	(12.70)	(125.49)	(13.24)	(14.15)	(14.59)	(16.34)
	[2.6%]	[-22.6%]	[3.2%]	[3.2%]	[-1.1%]	[3.0%]
Mean	188.98	395.7	242.4	255.8	232.91	262.91
Observations	6708	6708	6708	6708	6708	6708

Notes. This table reports the point estimates and the standard errors for θ^{simple} from Equation 3. The dependent variable is the number of maltreatment allegations per 10,000 children by child characteristics: race, gender, and age. Young children refer to those younger than the median age of seven, whereas old children refer to those older than seven. Change rates from the pre-PDMP means are reported in the square brackets. Standard errors in parentheses are clustered at the state level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

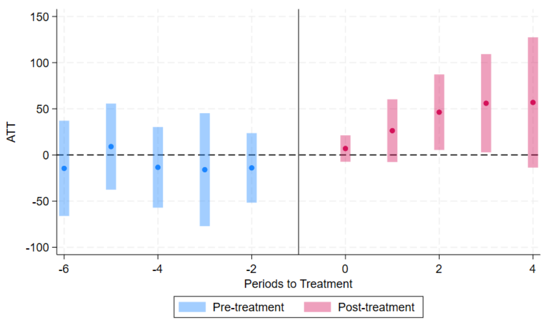
Figure A3: Event Study Results for Mandatory PDMP by Child Characteristics



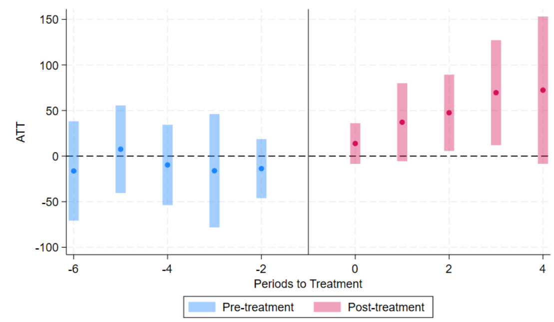
(a) White



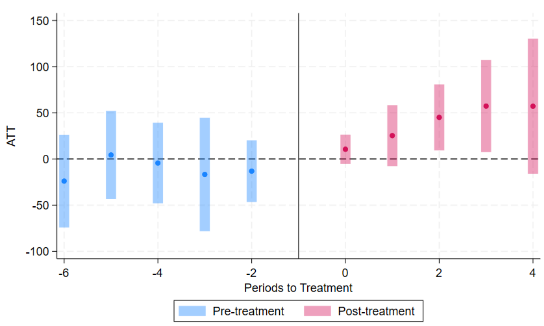
(b) Black



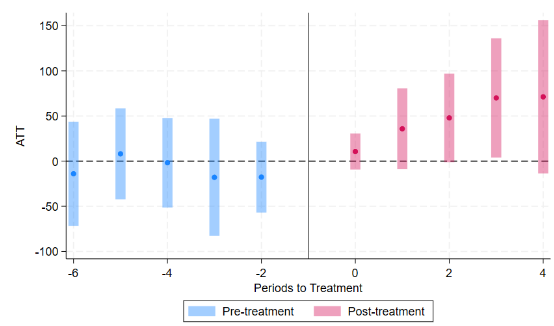
(c) Male



(d) Female



(e) Young



(f) Old

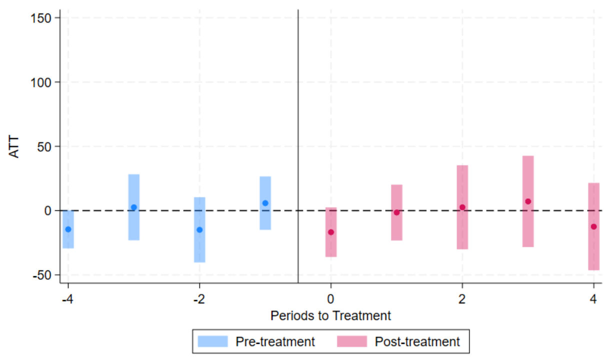
Notes. This figure reports point estimates and 95 percent confidence intervals on $\theta^{event}(e)$ from Equation 2. The dependent variable is the number of maltreatment allegations per 10,000 children by child characteristics: race, gender, and age. Young children refer to those younger than the median age of seven, whereas old children refer to those older than seven. Standard errors are clustered at the state level.

Table A5: Difference-in-Differences Results for Mandatory PDMP by Child Characteristics

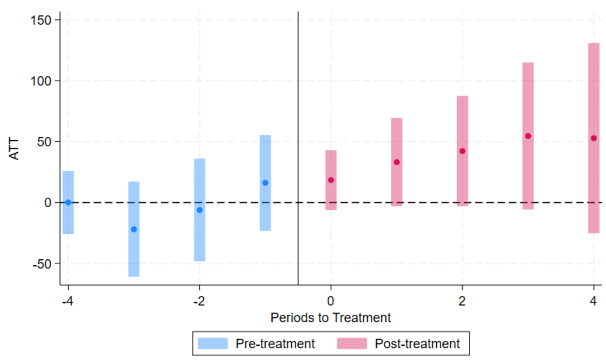
	(1) White	(2) Black	(3) Male	(4) Female	(5) Young	(6) Old
ATT	47.54***	87.06	36.75**	45.89**	37.29**	44.87**
	(17.87)	(68.87)	(16.27)	(19.62)	(15.83)	(21.10)
	[23.3%]	[21.9%]	[14.7%]	[17.4%]	[15.8%]	[16.3%]
Mean	203.65	397.95	250.46	263.29	235.92	275.58
Observations	7716	7716	7716	7716	7716	7716

Notes. This table reports the point estimates and the standard errors for θ^{simple} from Equation 3. The dependent variable is the number of maltreatment allegations per 10,000 children by child characteristics: race, gender, and age. Young children refer to those younger than the median age of seven, whereas old children refer to those older than seven. Change rates from the pre-PDMP means are reported in the square brackets. Standard errors in parentheses are clustered at the state level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure A4: Event Study Results for Allegations Using Never-Treated as Controls



(a) Modern PDMP



(b) Mandatory PDMP

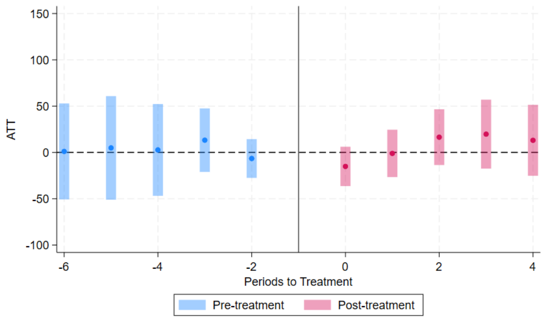
Notes. This figure reports point estimates and 95 percent confidence intervals on $\theta^{event}(e)$ from Equation 2. Counties that did not implement PDMPs during the sample period were used as the control group. The dependent variable is the number of maltreatment allegations per 10,000 children. Figure (a) presents the results of modern PDMP. Figure (b) presents the results for mandatory PDMP. Standard errors are clustered at the state level.

Table A6: Difference-in-Differences Results for Allegations Using Never-Treated as Controls

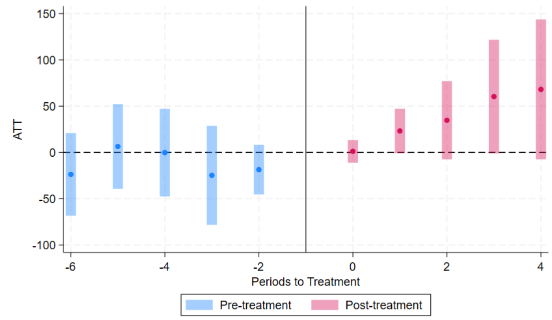
	(1) Modern	(2) Mandatory
ATT	-4.23	38.87**
	(11.28)	(19.39)
	[-1.7%]	[15.0%]
Mean	250.52	259.23
Observations	6708	7716

Notes. This table reports the point estimates and the standard errors for θ^{simple} from Equation 3. Counties that did not implement PDMPs during the sample period were used as the control group. The dependent variable is the number of maltreatment allegations per 10,000 children. Column (1) presents the results for modern PDMP. Column (2) presents the results for mandatory PDMP. Change rates from the pre-PDMP means are reported in the square brackets. Standard errors in parentheses are clustered at the state level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

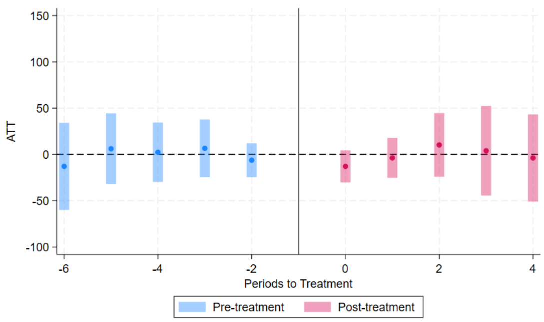
Figure A5: Event Study Results for Alternative Covariates



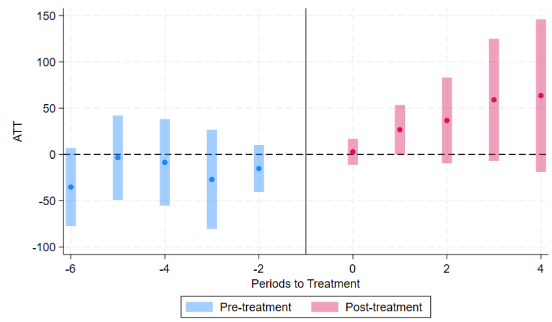
(a) Modern, Demographic



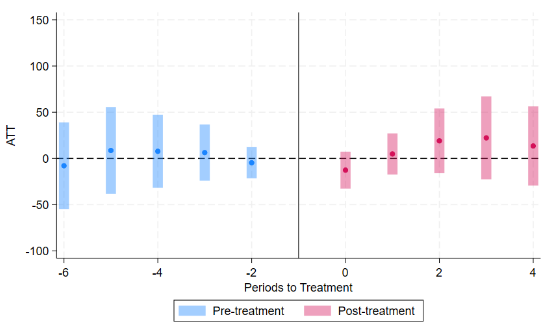
(b) Mandatory, Demographic



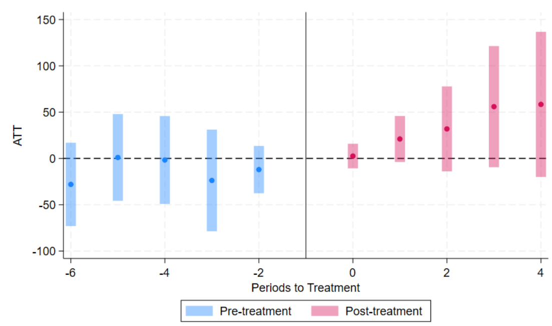
(c) Modern, Economic



(d) Mandatory, Economic



(e) Modern, No Covariate



(f) Mandatory, No Covariate

Notes. This figure reports point estimates and 95 percent confidence intervals on $\theta^{event}(e)$ from Equation 2. The dependent variable is the number of maltreatment allegations per 10,000 children. Figure (a), (c), and (e) report the results for modern PDMPs, whereas Figure (b), (d), and (f) report the results for mandatory PDMPs. Figure (a) and (b) report the estimates using demographic variables as the only covariates. Figure (c) and (d) report the estimates using economic variables as the only covariates. Figure (e) and (f) report the estimates without any covariate. Standard errors are clustered at the state level.

Table A7: Difference-in-Differences Results for Alternative Covariates

	(1) Modern Demographic	(2) Modern Economic	(3) Modern No Control	(4) Mandatory Demographic	(5) Mandatory Economic	(6) Mandatory No Control
ATT	6.39	-1.32	9.19	34.87**	35.44*	31.75*
	(12.46)	(14.87)	(14.74)	(17.29)	(19.64)	(18.93)
	[2.5%]	[-0.5%]	[3.7%]	[13.5%]	[13.7%]	[12.2%]
Mean	250.52	250.52	250.52	259.23	259.23	259.23
Observations	6708	6708	6708	7716	7716	7716

Notes. This table reports the point estimates and the standard errors for θ^{simple} from Equation 3. The dependent variable is the number of maltreatment allegations per 10,000 children. Columns (1), (2), and (3) report the results for modern PDMPs, whereas Columns (4), (5), and (6) report the results for mandatory PDMPs. Columns (1) and (4) report the estimates using demographic variables as the only covariates. Columns (2) and (5) report the estimates using economic variables as the only covariates. Columns (3) and (6) report the estimates without any covariate. Standard errors in parentheses are clustered at the state level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$